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How does left-digit bias affect price rigidity in firms?

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## 1 Abstract

I investigate how left-digit bias affects supply side decisions - in particular how it affects how rigid certain price-point endings are to cost increases. We construct a model of a profit-maximizing firm facing a left-digit biased demand curve and show that optimal prices are more rigid at 99-ending points - that is, the cost change required for the optimal price to change is greater. We then use Dominick's Dataset (data from a defunct grocery store that operated in the Chicago area) to examine whether 99 cent endings actually increase rigidity. We find significantly greater rigidity for 99-ending prices, and about half of the effect is present for 9-ending prices.

## 2 Introduction

Firms have long known that consumers do not perceive price linearly. Most firms believe, rightly so, that the difference in perceived price between pricing a good at 5.99 and 6.00 is greater than the difference between 6.00 and 6.01. This phenomenon has been termed "Left-Digit Bias." Formally, individuals exhibit left-digit bias if they react proportionally more (in terms of changes in demand) to changes in the leftmost digit of a price compared to the other digits. With left-digit bias, we expect to see a greater drop in demand moving from 5.99 dollars to 6.00 compared with the drop moving from 6.00 to 6.01.

Left-digit bias is precisely the reason why we see a disproportionate amount of 99-ending prices, whether it be in stores or on online platforms. This is because, as the model section will explain later, using a price that ends with 99-cents as opposed to its 00-ending neighbor significantly increases demand but only slightly decreases profit margins, leading to more overall profit.

Several studies have tried to estimate the magnitude of left-digit bias. For instance, Strulov (2021) analyzed consumer demand and price data from the top 25 largest US companies and found a left-digit bias parameter of around 0.2, which means that 20 percent of the downward slope of the demand curve comes from the discontinuous demand jump when the price crosses a dollar. The "20 percent" means that the size of the jump in demand that arises from changing a price from 99-ending to 00-ending by raising the price by 1 cent is 20 percent as large as the size of the demand jump that arises from raising a price by one full dollar. Other literature found larger values of left-digit bias. For example, "Left-Digit Bias at Lyft" by John List et al. (2023) found that the magnitude is 0.5 (which means that 50 percent of the downward slope of the demand curve is accounted for by the discontinuous jump when changing the left-digit).

In the case of Lyft, the high magnitude of left-digit bias has implications for optimal pricing that all prices should end with 99 cents. Studies that found smaller magnitudes of left-digit bias, such as Strulov's as mentioned earlier, found "missing prices" at the low cent values - meaning that there are prices such as 5.05 which would never be optimal in the face of left-digit bias. This is because the firm could slightly decrease the price to go under the dollar threshold and generate substantially more sales while sacrificing relatively little per unit.

With either result, we can expect 99-cent endings to be used disproportionately compared to other price-point endings. Because firms determine the optimal price through considering the demand they face as well as their costs, it intuitively follows that the 99 cent ending is optimal for a wider range of costs. Thus, should we assume that costs rise at a constant rate, this would mean that the length of time that a price stays at 99 cents should be longer than the time that a price stays at another price-point endings. We will formally prove this through our model described in the next section.

There is some literature on price point rigidity as well and how it relates to left-digit bias. In particular, Levy (2011) conducted an analysis of scanner-level data using the same dataset this paper aims to use: Dominick’s dataset. Through his investigation of how the 99-ending price spells (the duration of time that a price does not change) compares to non-99 cent ending spells, he found that, on average, 99-ending prices lasted around 50 percent longer than their non-99 ending counterparts. Moreover, the investigation extends to examining both upward and downward price rigidity, and finds that 99-cent endings are more rigid upwards than downwards. This is likely due to the fact that the firm recognizes that to increase a 99 ending price requires the dollar digit to increase - which would substantially reduce demand.

This paper aims to extend the analysis conducted by Levy and construct a formal model to explain the results that it found from the data. In particular, this paper aims to find whether 99-ending prices are more robust to cost increases than their non-99 ending counterparts. For example, if upstream suppliers make deals or contracts with companies which lead that company’s cost to remain stable for longer as well as mandate that the company sells the good at an ”attractive” price such as one ending with 99 cents, then the greater rigidity of 99-ending prices does not necessarily come from greater robustness from cost increases.

With more literature and research on left-digit bias, there is no doubt that more and more sellers take advantage of left-digit bias. In fact, Strulov (2021) found that the top 25 firms respond to the left-digit bias phenomenon by setting around 30-40 percent of their prices to end with 99 cents. On the contrary, Dominick’s dataset contains only around 15 percent of all observations that end with 99 cents. The difference is likely due to the 30-year difference between current datasets and Dominick’s. Thus, it is

perhaps true that more and more stores are taking advantage of consumers' left digit bias to set 99-ending prices. Moreover, the rapidly decreasing use of cash in favor of cards and contactless payment methods reduces the cost of pricing items at non-round numbers, a potential factor in explaining the increase in 99-cent endings.

Investigating how firms respond to consumers' left digit bias is crucial to understanding the welfare effects (to consumers, firms and overall) of left-digit bias in equilibrium. In particular, if we find that firms are more rigid (less reactive) to cost changes, this would mean that quantity demanded is not as responsive to cost changes as in the scenario where prices are not rigid. Imagine the extreme scenario where prices are completely rigid at 99-cent endings, meaning that prices would not increase for a very large range of costs, until the price jumps exactly one dollar upwards to the next 99-ending. The socially optimal equilibrium quantity is a continuous function of the production cost under perfect competition. At the tail end of a price spell, the cost would be much higher than at the beginning of the price spell, but the equilibrium quantity stays the same, which would suggest that the equilibrium quantity is too high relative to the socially optimal quantity. Right after the price jumps, the cost would be the lowest it would be within that price spell, which means that the equilibrium quantity is too low relative to the socially optimal quantity. Of course, the welfare effects are more complicated to analyze under non-perfect competition. (Strulov, 2023)

Price rigidity and price jumping stemming from left-digit bias would also have crucial implications on competition between firms. Strategic behavior depends a lot on the extent of a firm's knowledge of competitor's cost structure. Knowledge of a firm's cost structure can usually be deduced from their pricing behavior. However, with more rigid pricing, specifically for 99-cent endings, a wider range of costs is optimal, making it more difficult for competing firms to pinpoint any one firm's cost. Decreasing the

knowledge of competing firm's costs can change competitive behavior in many ways. For example, incumbent firms may be more cautious to engage in price wars due to less certainty regarding their competitors' costs.

In Section 3, I develop a model where firms maximize profit in the face of a left-digit biased downward sloping demand to make the prediction that 99-ending prices are more rigid than non-99 ending prices. In section 4, I discuss the data that I use and how I manipulate it to conduct analysis on the aforementioned rigidity. In Section 5, I discuss the results and econometric analysis that I use. Lastly, Section 6 summarizes and discusses possible extensions.

### 3 Model

We construct a model where we consider a firm with non-zero market power. The firm faces a downward sloping, left-digit biased demand curve, where consumers' demand depends on their perceived price.

$$\text{Consumer demand function: } D(p) = a - bp_{per}$$

The perceived price is a function of the price and the floor of the price. The consumer puts weight  $\theta$  on the floor of the price, and  $1 - \theta$  on the actual price itself.

$$p_{per} = \theta \lfloor p \rfloor + (1 - \theta)p$$

For  $\theta > 0$ , this means that the perceived price is discontinuous in the price, specifically at the integer dollar points. For example, for  $\theta = 0.5$ , equal to the value found by List

(2023),  $p_{per}(5.99) = 0.5 * 5 + 0.5 * 5.99 = 5.495$  and  $p_{per}(6.00) = 0.5 * 6 + 0.5 * 6 = 6.000$ .

Putting this together to obtain the consumer demand function:

**Consumer demand function:**  $D(p) = a - b[\theta \lfloor p \rfloor + (1 - \theta)p]$

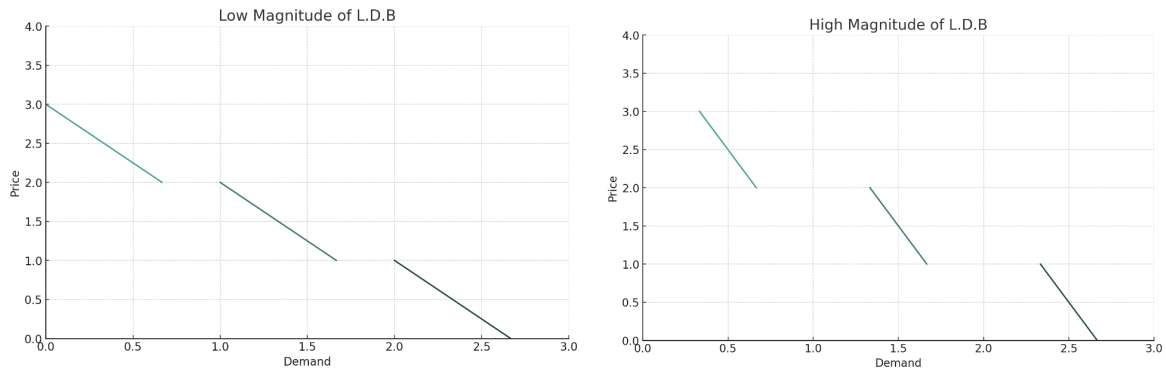


Figure 1: Figure of inverse demand curve under high and low magnitudes of left-digit bias

Figure 1 shows the inverse left-digit biased demand curve. In both cases, as price increases above an integer dollar value, the demand jumps discontinuously downwards, shown by the gap in the demand curve when the price is at an integer value. In the case of the low-magnitude left-digit bias, the discontinuity is smaller, whereas in the case with high-magnitude left-digit bias, the discontinuity is larger. The figure also sheds light on the abundance of 99-endings used by firms - should a firm consider pricing a good at a price with a low-cent ending (such as 6.15), the firm may be attracted to the potential to capture much greater demand by lowering the price to just under the integer threshold.

Now that we have established the nature of the demand curve that the firm faces, we discuss the nature of the demand cost structure that the firm has. We assume that the firm produces units that have cost equal to a constant  $c$ . The firm then sells at the

price that profit-maximizes with respect to price ( $p$ )

We attempt to show through our model that prices that end with 99 cents are more rigid than prices that do not, where rigidity refers to the size of the cost increase necessary to change the optimal price. First, we demonstrate that for prices that do not end with 99 cents (suppose that it ends with  $xx$  cents where  $xx \neq 99$ ) any cost increase changes the optimal price (no price rigidity). In the space below, I show that the difference in the cost that would induce the optimal price to be  $d + 0.xx$  where  $xx \neq 99$  and  $d + 0.xx + 0.01$  is only 0.02, demonstrating low rigidity.

$$\pi(d + 0.xx) = \pi(d + 0.xx - \varepsilon)$$

$$\begin{aligned} (d+0.xx-c)[a-b(\theta d+(1-\theta)(d+0.xx))] &= (d+0.xx-c-\varepsilon)[a-b(\theta d+(1-\theta)(d+0.xx-\varepsilon))] \\ &= (d+0.xx-c)[a-b(\theta d+(1-\theta)(d+0.xx-\varepsilon))] - \varepsilon[a-b(\theta d+(1-\theta)(d+0.xx-\varepsilon))] \\ &= (d+0.xx-c)[a-b(\theta d+(1-\theta)(d+0.xx))] + (d+0.xx-c)[b(1-\theta)] - \varepsilon[a-b(\theta d+(1-\theta)(d+0.xx-\varepsilon))] \end{aligned}$$

$$\Rightarrow b(1-\theta)(d+0.xx-c) = a - b[\theta d + (1-\theta)(d+0.xx)]$$

$$C_i^{opt} = \frac{2(d+0.xx) - \frac{1}{b(1-\theta)}a + \frac{\theta}{1-\theta}d}{b(1-\theta)}$$

$$C_i^{opt} = 2(d+0.xx) - \frac{1}{b(1-\theta)}a + \frac{\theta}{1-\theta}d$$

Now we find the cost that would make  $d + 0.xx + 0.01$  the optimal price.

$$\pi(d + 0.xx + 0.01) = \pi(d + 0.xx + 0.01 - \varepsilon)$$

$$\begin{aligned} (d + 0.xx + 0.01 - c)[a - b(\theta d + (1 - \theta)(d + 0.xx + 0.01))] &= (d + 0.xx + 0.01 - c - \varepsilon) \\ &[a - b(\theta d + (1 - \theta)(d + 0.xx + 0.01 - \varepsilon))] \end{aligned}$$

$$\begin{aligned}
&= (d+0.xx+0.01)[a-b(\theta d+(1-\theta)(d+0.xx+0.01))]-\varepsilon[a-b(\theta d+(1-\theta)(d+0.xx+0.01-\varepsilon))] \\
&= (d+0.xx+0.01)[a-b(\theta d+(1-\theta)(d+0.xx+0.01))] + b\varepsilon(1-\theta)(d+0.xx+0.01-c) \\
&\quad -\varepsilon[a-b(\theta d+(1-\theta)(d+0.xx+0.01))] \\
&\Rightarrow b(1-\theta)(d+0.xx+0.01-c) = a-b[\theta d+(1-\theta)(d+0.xx+0.01)] \\
&\Rightarrow C_f^{opt} = \frac{2(d+0.xx+0.01) - \frac{1}{b(1-\theta)}a + \frac{\theta}{1-\theta}d}{b(1-\theta)} \\
&\quad C_f^{opt} - C_i^{opt} = 0.02
\end{aligned}$$

So we see that prices that do not end in 99-cents do not exhibit a great deal of rigidity. Now, we constrast that with prices that end in 99 and attempt to show greater rigidity.

**Case 1:** Indifference between  $d + 0.99$  and  $d + 0.99 - \varepsilon$  where  $d$  is an integer.

$$\begin{aligned}
&\pi(d+0.99) = \pi(d+0.99-\varepsilon) \\
&(d+0.99-c)[a-b(\theta d+(1-\theta)(d+0.99))] = (d+0.99-c-\varepsilon)[a-b(\theta d+(1-\theta)(d+0.99-\varepsilon))] \\
&= (d+0.99-c)[a-b(\theta d+(1-\theta)(d+0.99))] - \varepsilon[a-b(\theta d+(1-\theta)(d+0.99-\varepsilon))] \\
&= (d+0.99-c)[a-b(\theta d+(1-\theta)(d+0.99))] + (d+0.99-c)[b(1-\theta)] - \varepsilon[a-b(\theta d+(1-\theta)(d+0.99-\varepsilon))]
\end{aligned}$$

Since  $\varepsilon$  is arbitrarily small, the inner  $\varepsilon$  can be omitted.

$$\begin{aligned}
&\Rightarrow b(1-\theta)(d+0.99-c) = \varepsilon[a-b(\theta d+(1-\theta)(d+0.99))] \\
&\Rightarrow b(1-\theta)(d+0.99-c) = a-b(\theta d+(1-\theta)(d+0.99))
\end{aligned}$$

$$\Rightarrow b(1 - \theta)(d + 0.99 - c) = a - b\theta d - b(1 - \theta)(d + 0.99)$$

$$\Rightarrow b(1 - \theta)(d + 0.99) - b(1 - \theta)c = a - b\theta d - b(1 - \theta)(d + 0.99)$$

$$c^{opt} = \frac{b(1 - \theta)(d + 0.99) - a + b\theta d}{b(1 - \theta)}$$

$$c^{opt} = 2(d + 0.99) - \frac{1}{b(1 - \theta)}a + \frac{\theta}{1 - \theta}d$$

For a sanity check, we examine the expression we obtain. We find that the higher the integer number that the 99-cent price was initially (the XX in XX.99), the higher the cost has to be for that price to be optimal.

Now, we have found the lowest possible optimal cost that resulted in the optimal price ending with 99 cents. Now we must find the minimum cost at which the the optimal price would be higher than  $d + 0.99$ . This means that the optimal price must take the form of  $d + 1.xx$  where  $xx$  is the cents value from 00 to 99. Should  $d + 1.xx$  be the optimal price, this means that the firm is indifferent between pricing at  $d + 1.xx$  and  $d + 1.xx - \epsilon$

Indifference between  $d + 1.xx$  and  $d + 1.xx - \epsilon$

$$\pi(d + 1.xx) = \pi(d + 1.xx - \epsilon)$$

$$(d + 1.xx - c)[a - b(\theta(d + 1) + (1 - \theta)(d + 1.xx))] = (d + 1.xx - c - \epsilon)[a - b(\theta(d + 1) + (1 - \theta)(d + 1.xx - \epsilon))]$$

$$= (d + 1.xx - c - \epsilon)[a - b(\theta(d + 1) + (1 - \theta)(d + 1.xx - \epsilon))]$$

$$= (d + 1.xx - c)[a - b(\theta(d + 1) + (1 - \theta)(d + 1.xx))] - \epsilon[a - b(\theta(d + 1) + (1 - \theta)(d + 1.xx - \epsilon))]$$

$$= (d + 1.xx - c)[a - b(\theta(d + 1) + (1 - \theta)(d + 1.xx))] + \epsilon b(1 - \theta)(d + 1.xx - c) - \epsilon[a - b(\theta(d + 1) + (1 - \theta)(d + 1.xx))]$$

$$\Rightarrow b(1 - \theta)(d + 1.xx - c) = \epsilon[a - b(\theta(d + 1) + (1 - \theta)(d + 1.xx))]$$

$$b(1 - \theta)(d + 1.xx) - b(1 - \theta)c = a - b(\theta(d + 1)) - b(1 - \theta)(d + 1.xx)$$

$$c_f^{opt} = 2(d + 1.xx) + \frac{\theta}{1 - \theta}(d + 1) - \frac{1}{b(1 - \theta)}a$$

$$c_f^{opt} - c_i^{opt} = 2(1.xx - 0.99) + \frac{\theta}{1 - \theta}$$

So as we can see, for all  $\theta > 0$ ,  $c_f^{opt} - c_i^{opt}$  is positive and larger than 0.02. The model predicts greater price rigidity for prices that end with 99 compared to prices that do not. As one can see, the higher the value of the theta, the higher the difference in cost, which means the more rigid it is. This makes intuitive sense, as this suggests that the more left-digit bias consumers are, the more firms aim to take advantage of pricing at 99-cent ending thresholds as the decrease in demand that arises from increasing the left digit to the next integer is relatively larger - it is profitable to endure the small margins to retain the larger sales.

**99 cent:**  $C_f^{opt} - C_i^{opt} = 2(1.xx - 0.99a) + \frac{\theta}{1 - \theta}$

**If  $\theta = 0$ ,**  $2(1.xx - 0.99) + \frac{\theta}{1 - \theta} = 0.02$  when  $\theta = 0$

This is because the optimal price will be only one cent higher due to the lack of jump discontinuity in the demand curve.

$$= 0.02$$

However, the optimal price being  $p = d + 0.99$  does not necessarily mean that the firm is indifferent between  $p = d + 0.99$  and  $p = d + 0.99 - \epsilon$ . Since the demand curve is not a continuous in  $p$ , this means that it could be a corner solution, and in fact  $\pi(d + 0.99) > \pi(d + 0.99 - \epsilon)$ . This thus means that  $\pi(d + 0.99) > \pi(d - 0.01)$ . Either way, we know that if  $p = d + 0.99$  is optimal, then both  $\pi(d + 0.99) \geq \pi(d + 0.99 - \epsilon)$  and  $\pi(d + 0.99) \geq \pi(d - 0.01)$ . At least one of the two inequalities must be equal at

the lowest possible cost that makes the price  $d + 0.99$  optimal.

## 4 Data

We use Dominick’s Dataset. This dataset comes from a defunct grocery store in Chicago. The grocery store is currently no longer in operation and released their data from 1989 to 1997 - around 8 years worth of data. There are over 90 stores all within the Chicago Metro area, with over 20,000 unique products. There is scanner level data on prices, quantity sold and profit margins (and therefore costs can be deduced).

Each store of Dominick follows a price scheme that falls neatly into four categories: Low, Medium, High and Cub-Fighter, with each of the types responding to their environment to maximize profit. Within each type, the stores rather closely follow each other’s prices. We find evidence of this through analyzing the correlation between prices in stores that are of the same pricing category and find an average correlation of around 0.99. However, even across the different pricing categories, the stores’ pricing do not differ that much, with a correlation coefficient of over 0.98 for most pairs.

Due to data size constraints as well as the demonstrated similarity in pricing patterns between stores, especially between stores of the same pricing type, we randomly select four stores, one of each pricing type, within the 93 stores present in the dataset. This method was also employed by Levy (2011) in his analysis. In our results, we selected stores 73,86,122, and 137. (only 90 out of the stores numbered 1 to 160 were present in the data) We find that, as mentioned before, the correlation between any two of the stores selected is at least 0.98, demonstrating that overall pricing patterns do not differ greatly between the stores.

After aggregating the data from the four stores and across the 27 categories, we subset

the data further before we perform further analysis on the relationship between price point endings and cost increase rigidity.

It is important to note that while the dataset contains quantity sales, price and profit data, the data only appears for weeks where there is non-zero demand for that particular store-good-week combination. Therefore, for goods with low demand, it is common to find that a small proportion of weeks have non-zero prices, which means that if we analyze a price spell (a chain of weeks where the price remains the same) and examine the cost increases during that price spell, it is rather difficult to tell in which week the price was changed, and to what extent the costs changed between the weeks in which there was no price or cost data recorded. While using the analysis tools that we use in Section 5 still gives us unbiased estimates of price rigidity, the noise of the estimates would be much greater should I include UPCs that have very few weeks of data.

In order to address this, we subset the 13,000 UPCs, only keeping the ones where there are at least 100 (out of 400) weeks of data and at least 5 unique price values across the four stores. With at least of 100 weeks of data, this means that at least 25 percent of the weeks have price data. This means that on average, the weeks with available data could be weeks 1,5,9 and 13. If the price and/or cost changed somewhere between week 6 and 8 (meaning 5 and 9 were different prices), guessing that the price changed in week 7 would result in the estimate being 1 week off at most. We find that 5,293 have at least 100 weeks of available data.

Moreover, we also subset the data to include only UPCs which have at least 3 unique prices. This is because we are unable use the week 1 price and week 400 price as part of the analysis - we do not know when the price changed before arriving at the week 1 price, and we do not know at which week after week 400 the price changes from the

last observed price. Since UPCs with at least 100 weeks of data are more likely to have more unique prices, this filtration leaves us with 99 percent of the data points after the last filter - 5250 rows.

We exclude price changes that are special sales or deals. Levy (2011) also employs this filtering. This is because deals last for a set amount of time, which means that the change of the price back to the pre-sale price is likely not responding to any cost-change. Fewer than one-fifth of all price observations are part of special deals or sales.

Lastly, we perform the analysis only on price increases. Within the dataset, 56 percent of price changes are price increases, which means that nearly half of the price changes are price decreases. Should we want to investigate how much the cost changes within a single price spell, we want to exclude the times where the price decreases, as it usually happens as a result of decreasing costs. Since the proportion of price increases is nearly the same as that of price decreases, the larger cost increases within a singular price spell may be offset by a larger cost decrease within another price spell where the subsequent change is a price decreases. Indeed, I find that while the average cost change within a price spell is positive regardless of whether we subset to price increases, the average cost increase is approximately 10 times larger when we subset for price increases, and the 99-ending effect is also larger.

## 5 Results

We first investigate the distribution of 99-ending prices in the full set of data. In Figure 1, we see that a disproportionate amount of prices end with 99-cents. Should cent endings be uniformly distributed, this should mean that the proportion of 99-ending is

around 1 percent. In contrast, we find that over 14 percent of prices end with 99 cents. Notably, a much higher than uniform proportion of prices end with 9 as the hundredth digit - with over 60 percent of all prices ending with 9 as the hundredth digit.

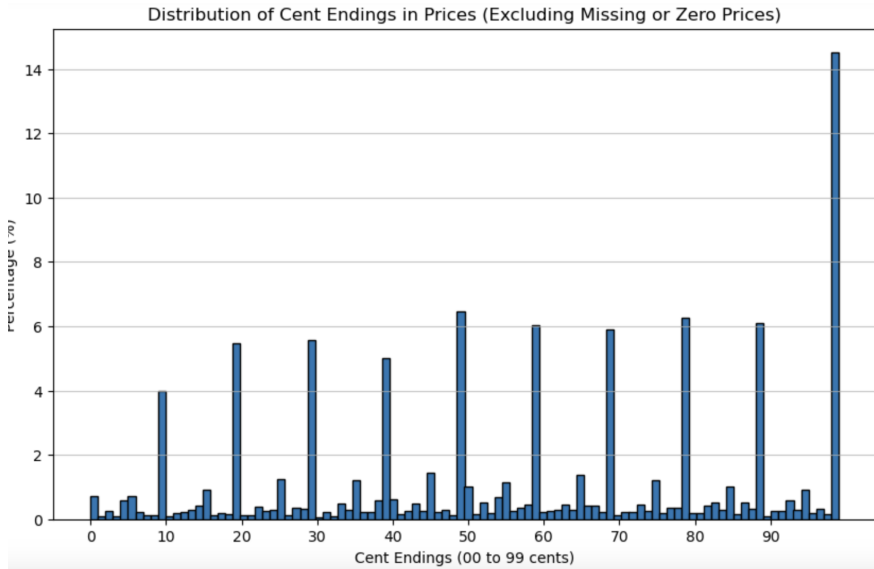


Figure 2: Distribution of price point endings in the full data set. I perform this analysis using all of the stores and data available, and obtain the "cents" digit of each price. I then find the distribution of the two last digits from 00 to 99 and plot them in bar-chart form.

This shows evidence the firm is, at least to some extent, taking advantage of left-digit bias in consumers.

Within each category, we find significant heterogeneity. Some categories have as low as 2 percent of their prices ending with 99-cents, whereas some of them have as much as 40 percent.

Now we move on to analyzing how much cost rises throughout each price spell. A price spell is defined as a period of time where there are no price changes. For example, if in Weeks 180,181,182, and 183 for a certain product and store have prices 4.99,5.19,5.19,5.29, the 5.19 dollar price spell lasts from week 181 to week 182. Should

our model predictions be correct, we should see that cost increases within a price spell are greater when the price ends with 99 cents. That is, a price that ends with 99 will be optimal for a larger range of costs than prices that do not.

First, we find the "cost gap" of each price spell - the difference between the absolute cost in the last observation of the price spell and the first observation of the price spell. We also then create a dummy variable which serves as an indicator variable to perform regressions on.

$$(1) \text{ first-last costdiff}_i = \alpha + \beta \text{indicator}_{99_i} + \epsilon_i$$

First, we conduct the naive regression, where we simply regress the cost-gap as the response variable and the  $\text{indicator}_{99}$  as the explanatory variable. We find a moderate and significant (at the 1 percent level) value of just under 1 cent. This suggests that, on average, the cost gap of prices that end with 99 is nearly 1 cent higher on average than the gap of prices that do not end with 99. Although this may seem small, the intercept of the regression is only 0.7 cents, which means that the mean change in costs within a price spell is only 0.7 cents, and being a 99-cent ending price makes the average change around 1.5 cents.

Right away, one may notice that the coefficient and the intercept are surprisingly small. The mean cost change is an increase of only 0.7 cents for non-99 ending prices, and even with 99-ending prices, the mean cost change is only around 1.5 cents. To understand why the cost changes are much smaller than one may expect, we first investigate the proportion of price changes that are price increases, and find that just above half of the price changes are price increases (only 56.5 percent). This means that price fluctuation is perhaps more common than one may expect.

It is most likely a good idea to exclude price decreases from the analysis. Since the model predicts that 99-ending prices have a larger range of costs that would make the 99-ending price optimal in comparison to other prices, this also means that in price decreases, the cost would be able to decrease more before the optimal price decrease. Thus, the greater rigidity both upwards and downwards may cancel out, muting the effect of the 99-ending price. Notably, we will see even when we lump together price increases and decreases that the *indicator*<sub>99</sub> variable still has a coefficient that is statistically significant. This could be due to the fact that there are still more price increases than decreases, which could mean that the upward price rigidity could outweigh the downward price rigidity.

However, even sub-setting for price increases, we still find that the cost gap is surprisingly small, with a large proportion of the cost increases being zero (around 77 percent). Examining the data closely, this has to do with the fact that since the dataset includes only weekly observations, any changes in costs usually result in changes in price within the same week. Thus, subtracting the cost in the last observation of the price spell from the first cost observation of the price spell would result in an underestimate in the full range of costs that would make the price optimal.

An alternative way to measure the cost increase would be to compare the cost of the first week within the price spell and the first week of the following price spell. This would address the underestimate in the range of costs that would make the price optimal. One may argue that this overestimates what we are trying to measure, as the new cost caused the price to be revised upwards, which means that it is no longer within the range that would make the old price optimal. This is certainly true, but the same is true for the cost observation at the beginning in the first week of the old price. The

cost observation in the first week of the price spell is not necessarily the lowest cost that would make that price optimal - the lowest possible is somewhere between the cost observed on the last week of the previous price spell and the first week of the new price spell.

Perhaps the most compelling reason to use a comparison between the first week's cost of a price spell and the first week's cost of the next price spell is that, on average, it provides an accurate estimate of the range of costs that would make a price spell optimal. Using the previous method of comparing costs from the first and last week of a price spell would systematically underestimate the true cost range

Using first-first cost difference as the dependent variable on the subset of price spells that were followed by price increases (we call the variable "cost-diff" for short), we re-run the naive specification along with three other specifications of models of increasing complexity.

Table 1 below provides the results of the regression specifications. The first naive regressions (which is simply a difference of means) yields a coefficient of around 0.15 for the *indicator<sub>99</sub>* variable, and it is significant at 1 percent. This means that, on average, prices that end in 99-cents have cost ranges that are optimal for the price that are around 15 cents larger than prices that do not end with 99-cents. Notably, the intercept is around 10 cents, which means that non-99 ending prices have an optimal range of around 10 cents, whereas 99-ending prices have an optimal range of around 25 cents.

It is important to note that in the regression specifications that follow, I impose the zero-sum constraints on the other coefficients. This is done in order to avoid bias in

the indicator coefficient, which would be easily influenced by the choice of which category/store/interaction to drop.

In specification (3), we find it explains a much higher percentage of the variation in the response variable compared to the first specification. Conducting an F-test in comparison with specification (2), we find a p-value of nearly 0. This means that a significant amount of the variation in the cost difference can be explained the in different categories. Notably, we still find a significant estimate of around 12 cents.

In the specification (4), we add the *indicator<sub>9</sub>* variable. As we examined earlier, a significant amount of prices in the dataset end with 9 as the hundredths digit, even if they do not end with 99. Interestingly, we find a significant result for the *indicator<sub>9</sub>* variable, which means that prices that do not end with 99, but still end with 9 in the hundredths digit are still more cost-rigid than their non-9 ending counterparts. The result is moderately large at 6.6 cents and significant at the 1 percent level. The *indicator<sub>99</sub>* variable remains significant, however, implying that prices that end with 99 are optimal for a cost range that is around 15 cents wider than prices that do not end with 9, and 9 cents wider than the cost range for prices that end with 9 but not 99.

In specification (5), we add the interaction terms, where we allow the categories to interact with both the *indicator<sub>99</sub>* and the *indicator<sub>9</sub>* variables. Here, we still find a significant result for both the indicator variables, although the magnitude decreased. Here, the dependent variable is the difference in cost between the first week of a price spell and the first week of the following price spell. For all four specifications, we use a subset of the data from 1989-1997 across 4 randomly selected stores, one of each pricing type, with at least 100 weeks of price data with at least 5 unique prices (which has 5,250 unique products). We also subset to only price increases. For specifications

	(2)	(3)	(4)	(5)
intercept	0.1018*** (0.001)	0.0704*** (0.001)	0.0468*** (0.002)	0.0625*** (0.002)
indicator <sub>99</sub>	0.1529*** (0.004)	0.1262*** (0.004)	0.0875*** (0.004)	0.0309*** (0.007)
indicator <sub>9</sub>	—	—	0.0664*** (0.002)	0.0345*** (0.003)
category controls	No	Yes	Yes	Yes
store controls	No	Yes	Yes	Yes
indicator <sub>99</sub> interactions	No	No	No	Yes
indicator <sub>9</sub> interactions	No	No	No	Yes
$R^2$	0.008	0.062	0.067	0.085

Table 1: This table shows the regression coefficients for the 9-ending and 99-ending price variables across four different specifications. I data to includes only four randomly selected stores with at least three unique prices and 100 weeks of complete data. Then, found the magnitude of the cost increase within the time during which a price stays the same. Then, cost difference is regressed on the 99-ending indicator in various model complexities. For (3), and other later specifications, I create dummy variables for store and category and impose the zero sum constraints. For specification (4) and (5), I also included indicator dummies for 9-ending prices, and in (5), I allows the interaction term as well.

(3), (4) and (5), we create dummy variables for store and category and impose the zero sum constraints.

While the model prediction correctly predicts that prices that end with have a 99 have a wider range of costs that make the price optimal compared to non-99 ending prices, the model does not do so well in predicting the magnitude of the cost ranges. According to the model, the non-99 prices should have cost ranges of 2 cents. However, we find that across all specifications (found by the intercept value), the non-99 ending prices have cost ranges much larger than 2 cents. This could be due to menu costs - the fact that it is costly to change prices, and thus prices are not changed unless the difference in profit of the new price is greater than the the profit associated with the old price by larger than the menu cost.

For the 99-ending prices, if we take the median jump size (which refers to the median amount the price increases by), we get around 7 cents. If we use the 0.10 value of  $\theta$ , which is one of the lower-end values that Strulov (2023) suggested (since he found that

lower prices were subject to smaller values of left-digit bias), we get that the cost range should be:

$$c_f^{opt} - c_i^{opt} = 2(1.07 - 0.99) + \frac{0.10}{1 - 0.10} = 0.27$$

In fact, specification (2),(3) and (4) get quite close to this estimate produced by the model with estimate of cost-ranges of 0.25,0.20, and 0.19 respectively.

However, simply taking the cost difference between the first week of a price spell and the first week of the following price spell does not take into account the variation in costs in between the weeks. While one may argue that measuring the cost difference in the way that I did should truly uncover the full range of costs that make the price optimal, this only if true if costs behave in a monotone way - costs always rise. If this does not hold, costs at a week in between the two measurement points could be higher than at the endpoint.

A way to address this would be to measure the goodness-of-fit between a regression between the price and cost for each UPC. Should prices be more rigid to changes in cost, R-squared for the regression should be lower (prices can explain less of the variation in costs). However, looking at the UPC level will be too noisy, since some UPCs have few unique prices and incomplete data that covers all of the weeks. Thus, we aggregate on the category level, giving us 27 data points to work with. Therefore, the more price-rigid categories should find a lower R-squared value for the regression. The rigidity of the pricing in a certain category can be measured by the proportion of 99-ending prices in that category. Should a category have a low-proportion of 99-ending prices, this means that the 99-ending prices are optimal for a smaller range of

prices, mean that prices are less rigid. For each category, I find the R-squared value for each UPC and find the median R-squared value within that category. I regress the median R-squared value against the the proportion of 99-ending prices, as well as the proportion of 9-ending prices. We would expect a downward sloping line of best fit - the categories with higher proportions of 99-ending prices would have a lower share of the price variance explained by cost. This is certainly a possible extension that would provide further evidence of the model predictions.

## 6 Conclusion

I find that 99-ending prices are in fact more rigid than prices with other price point endings in Dominick's dataset. We use a left-digit biased demand curve model to find how the optimal price changes with cost. Here, we find that the range of costs that make a 99-ending price optimal is larger than the range of costs that would make prices with other endings optimal - which suggest that if costs rose at a somewhat constant rate, the prices that end with 99-cents would be stagnant for longer periods of time.

Indeed, the data bears this prediction. We find that under the naive specification, prices that end with 99 have greater differences in cost from the first week of the price spell to the first week of the next price spell (which is a proxy for the range of costs that make the price optimal). In particular, I find that the range of costs is approximately 15 cents wider for 99-ending prices; the average range of costs that make 99-ending prices optimal is around 25 cents whereas the range is only 10 cents for non-99 ending prices. Adding in covariates, the effect of the 99-cent decreases. In later specifications, we can see that part of the 99-ending rigidity is due to the rigidity in all 9-ending prices in general. In specifications 3 and 4, we can see that around half of the 99-cent

rigidity effect is absorbed by the 9-cent (in the hundredth digit) rigidity effect when we include it as a covariate. The greater price rigidity of 99-ending prices by a significant margin reveals that when firms take advantage of left-digit bias, prices changes are less frequent and price jumps are larger.

With the rise of cashless payments across the US, it is also plausible to argue that the magnitude of left-digit bias has increased. This is because individuals no longer have to take out 4 dollar bills from their wallet to pay 3.99 (reinforcing the notion that the price is in fact closer to 4 dollars than it is to 3 dollars). Perhaps expected, firms have also increased the proportion of 99-ending prices that they use. The larger the proportion of 99-ending prices, the more rigid they likely are. Thus, the 5-15 cent wider cost range (the estimates from the 1-3 specification) are likely lower than the difference in cost range in most stores today between 99-ending and non-99 ending prices. Should there be access to newer, more current pricing data, it would be interesting to see whether rigidity in 99-ending prices is even greater in response to a higher level of left-digit bias.

## 7 References

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