Online Supplementary Web Appendix

Zero-Ending Prices, Cognitive Convenience, and Price Rigidity

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<u>Appendix A</u>. Robustness tests for the Israeli CPI data

In the paper, we conduct several tests showing that 0-ending prices are more rigid than other prices at Israeli convenience stores.[1] Below we provide the results of several additional robustness tests, to show that the results we report in the paper are not driven by outliers.

In Table A1, we estimate regressions similar to the ones we report in column 4 of Table 1 in the paper. These regressions include a full set of control variables, in addition to the main independent variables. The dependent variable is a dummy that equals 1 if the price has changed and 0 otherwise. The list of independent variables includes a 0-ending price dummy which equals 1 if the previous price ended in 0, a 9-ending price dummy which equals 1 if the previous price ended in 9, a transaction-inconvenience index which equals the minimum number of coins/notes needed to pay the price, a dummy for convenience stores, an interaction of the convenience store dummy with the 0-ending dummy, with the 9-ending dummy, and with the transaction-inconvenience index, the price level which is calculated as the previous period price rounded to the nearest NIS, the log of the population of the town where the store is located, the socio-economic score of the town where the store is located, the share of women in the town where the store is located, the log of the distance of the town where the store is located from Tel-Aviv, the share of minority groups in the town where the store is located, and a sale dummy which equals 1 if the previous period price was a sale price. The regression also controls for product categories, the six regions of Israel, and the quarter in which the observation was taken. Standard errors are clustered at the level of the store where the observation was taken.

In column 1, we restrict the sample to goods with prices ≤ NIS 200. It is likely that higher prices are usually not paid with cash (Chen et al. 2019, Shy 2020), as the highest denomination bill in Israel is NIS 200. We find that the coefficient of the 0-ending price dummy is positive and significant ($\beta = 0.010, p < 0.01$), while the coefficient of the dummy for the 9-ending prices is negative and significant ($\beta = -0.045, p < 0.01$). We,

[1] Following Knotek (2011), we classify a store as a *superstore* if the CBS flags it as a supermarket, chain store, department store, or a drugstore. We classify a store as a *convenience store* if the CBS flags it as a small grocery store, gas station, kiosk, convenience shop, or a specialty shop such as a bakery, fruits/vegetables store, etc.

therefore, find that when we restrict the sample to prices up to NIS 200, then at superstores 0-ending prices are not more rigid than other prices, but 9-ending prices are.

The coefficient of the transaction inconvenience index is positive and significant ($\beta = 0.017, p < 0.01$), suggesting that an increase in the number of coins needed to pay the price is associated with a greater likelihood of a price change.

The interaction of the 0-ending dummy with the convenience-stores dummy is negative and significant ($\beta = -0.063, p < 0.01$). In convenience stores, therefore, 0-ending prices are more rigid than other prices even when we restrict the sample to prices of up to NIS 200 ($F = 92.9, p < 0.00$). The interaction of the 9-ending dummy with the convenience-stores dummy is positive and significant ($\beta = 0.030, p < 0.01$), implying that although 9-ending prices are also more rigid than other prices in convenience stores ($F = 3.28, p < 0.08$), they are less rigid in than in superstores. Further, in convenience stores, 9-ending prices are less rigid than 0-ending prices ($F = 35.1, p < 0.01$).

In column 2, we further restrict the sample. This time, we restrict the sample to prices that are ≤ NIS 4, to match it with the price level of the products we study at Dominick's ($1).[2] We find that in superstores, 0-ending prices are not more rigid than other prices ($\beta = 0.089, p < 0.01$), while 9-ending prices are ($\beta = -0.038, p < 0.01$). An increase in the number of coins needed to pay a price is associated with a higher likelihood of a price change ($\beta = 0.022, p < 0.01$), i.e., lower price rigidity.

The coefficient of the interaction of the 0-ending dummy with the convenience stores dummy is negative and significant ($\beta = -0.113, p < 0.01$), implying that in convenience stores 0-ending prices are more rigid than other prices ($F = 3.33, p < 0.07$). The coefficient of the interaction of the 9-ending dummy with the convenience stores dummy is positive ($\beta = 0.003, p < 0.01$). After taking into account the main effect, we still find that for prices smaller than NIS 4, 9-ending prices are more rigid than other prices also in convenience stores ($F = 5.68, p < 0.02$). For this level of prices, the rigidity of 0- and 9-ending prices are not statistically different ($F = 1.09, p > 0.29$).

[2] During the sample period, the average NIS/$ exchange rate was NIS 4.09 per $1.

In column 3, we restrict the sample to prices that can be paid with a single coin or a single note, e.g., all prices in the range of 4.95–5.04, or 19.95–20.04.[3] These are the most convenient prices and, therefore, the ones that are most likely to be paid with cash (Knotek 2008, 2011, 2019; Chen et al. 2019, Shy 2020). We find that in superstores, 0-ending prices are not more rigid than other ending prices ($\beta = 0.002, p < 0.01$), while 9-ending prices are ($\beta = -0.054, p < 0.01$). The interaction of convenience stores and 0-ending prices is negative and significant ($\beta = -0.071, p < 0.01$), while the interaction with 9-ending prices is positive and significant ($\beta = 0.018, p < 0.01$). Thus, when we restrict the sample to prices that can be paid with one coin/note, we find that in convenience stores both 0-ending prices ($F = 12.3, p < 0.01$) and 9-ending prices ($F = 3.4, p < 0.07$) are more rigid than other prices. 0-ending prices, however, are more rigid than 9-ending prices ($F = 12.0, p < 0.01$).

In column 4, we restrict the sample to regular prices, by removing the sale and bounce-back prices. A large stream of literature in macroeconomics has shown that at the aggregate level, regular price changes are more important than temporary price changes (i.e., sales). See, for example, Nakamura and Steinsson (2008), Eichenbaum et al. (2011), and Midrigan (2011). In this regression, we, therefore, check if our results remain qualitatively unchanged if we exclude the sale prices.

The results are again similar to the ones we report above. When we restrict the sample to regular prices, we find that 0-ending prices are not more rigid than other prices in superstores ($\beta = 0.008, p < 0.00$). The interaction of 0-ending prices with convenience stores, however, is negative and significant ($\beta = -0.053, p < 0.01$), implying that in convenience stores, 0-ending prices are more rigid than other prices ($F = 46.8, p < 0.01$). 9-ending prices are more rigid than other prices in superstores ($\beta = -0.047, p < 0.01$). The interaction of 9-ending prices with convenience stores, however, is positive and significant ($\beta = 0.036, p < 0.01$), implying that in convenience stores, 9-ending prices are not more rigid than other prices ($F = 2.5, p < 0.12$).

[3] This range of prices refers to the period after 2008. Before 2008, Prices in the range 4.98–5.02 could have been paid with a single coin.

In column 5, we estimate the regression using the full set of data, but replacing the linear probability model with a probit model. We find that using a non-linear estimation technique does not affect the results qualitatively. 0-ending prices are not more rigid than other prices in superstores, but they are more rigid than other prices in convenience stores. 9-ending prices are more rigid than other prices in superstores and convenience stores. In convenience stores, however, 0-ending prices are more rigid than 9-ending prices ($\chi^2 = 37.2, p < 0.01$).

In column 6, we focus on convenience stores and we add dummy variables for each possible price ending. We find that the coefficient of 0-ending is negative and statistically significant ($\beta = -0.056, p < 0.01$). Furthermore, in column 1 of Table A2, we compare the coefficient of 0-ending prices with the coefficients of prices with other endings. We find that 0-ending prices are significantly more rigid than prices with any other ending.

For completeness, in column 7 we focus on superstores. We find that the coefficient of 0-ending prices is negative and statistically significant ($\beta = -0.044, p < 0.01$). However, when we compare the coefficient of 0-ending prices with the coefficients of prices with other endings (column 2 of Table A2), we find that in most cases, the difference is not statistically significant. In other words, in convenience stores, prices that end in 0 are less likely to change than prices that end with any other ending. In superstores, 0-ending prices are not particularly rigid.

In column 8 we check if the results are robust to changing the definition of convenience stores. In the paper, we define a store as a convenience store if the CBS flags it as a convenience store, a small grocery, a kiosk, an open market stall, or a specialty store. For this test, we define a store as a convenience store only if the CBS defines it as a convenience store. We then estimate a regression using data only on observations from convenience stores. We had to drop the dummy for sales because the number of sales in convenience stores is too low. We find that both the coefficient of 0-ending prices ($\beta = -0.132, p < 0.01$) and of 9-ending prices ($\beta = -0.141, p < 0.01$) are negative and statistically significant. The difference between the two coefficients is not statistically different ($F = 0.27, p > 0.60$).

An alternative explanation for the frequent use of 0-ending prices at convenience stores is that retailers might be using them to save computation time. Before 2008, if a consumer bought three products that have a 9-ending price and pay in cash, then the cashier would most likely have to give him a 5-agora coin as a change. For example, if the consumer bought three products costing NIS 4.99, then the total price would be NIS 14.97 which would be rounded down to NIS 14.95. Therefore, if the consumer was to pay NIS 15 in cash, the retailer would have to give him a 5-agora coin as a change. This implies that using 0-ending prices could simplify the computations and enhance the transaction speed also at convenience stores.

To check the relevance of this type of transaction convenience, we focus on the sample of convenience stores and conduct two tests. First, we divide the convenience stores into those that are likely to have a till—convenience stores, small groceries and specialty stores, and those that are unlikely to have a till—kiosks and open market stalls. If transaction convenience played a significant role in the prevalence of 0-ending prices, then the stores that do not have a till would be more likely to use 0-ending prices than stores that have a till, since the till simplifies the calculations that the cashier has to perform.

We find that 90.0% of the prices at stores that are unlikely to have a till are 0-ending, compared to 63.8% at convenience stores that are likely to have a till. The difference is statistically significant (Wilcoxon rank-sum test $z = 195.1, p < 0.01$). Thus, it seems that transaction convenience might have played some role in the setting of 0-ending prices. Nevertheless, convenience stores that do not have a till still had over 60% 0-ending prices, suggesting that transaction convenience was not the only consideration for using 0-ending.

We can also test whether having a till affected the price rigidity of 0-ending prices. We focus on the sample of convenience stores and estimate a regression with the full set of control variables, as above. The main independent variables are a 0-ending dummy, a 9-ending dummy, a dummy for stores without a till, and interactions of the dummy for stores without a till with the dummies for 0-ending and 9-ending prices. The estimation results are given in the first column of Table A3.

We find that both 0-ending prices ($\beta = -0.062, p < 0.01$) and 9-ending prices ($\beta = -0.035, p < 0.01$) are more rigid than other prices at convenience stores. However, the coefficient of the interaction of the 0-ending dummy with the dummy for stores without a till is not statistically significant ($\beta = -0.026, p > 0.74$). The interaction of the 9-ending dummy with the dummy for stores without a till is also not statistically significant ($\beta = -0.070, p > 0.39$). The interaction of the transaction inconvenience score with the dummy for stores without a till is positive and statistically significant ($\beta = 0.010, p < 0.01$). Therefore, it seems that stores that do not use a till tend to maintain transaction-convenient prices unchanged for longer periods than convenience stores with a till. The absence of a till does not affect, however, the duration of 0-ending and 9-ending prices, suggesting that the main reason for setting such prices is not transaction convenience.

As a further test, we look at the shares and rigidity of 0-ending prices before and after 2008. After 2008, the 5-agora coin ceased to be a legal tender. Consequently, a consumer had to buy more 9-ending products before the retailer had to give him change: Before 2008, a consumer had to buy three 9-ending products before the price was rounded down to NIS 0.95. After 2008, the consumer had to buy 6 products before the price was rounded down to NIS 0.90. Thus, the transaction inconvenience of non-round prices became even less acute after 2008. Therefore, if the main reason for using 0-ending prices was transaction inconvenience, then after 2008 the share of 0-ending prices should have decreased significantly.

We find that the share of 0-ending prices indeed decreased slightly. At convenience stores with a till, it decreased from 65.5% to 61.8% (Wilcoxon rank-sum test $z = 22.8, p < 0.01$). At convenience stores without a till, it decreased from 91.7% to 87.2% (Wilcoxon rank-sum test $z = 29.4, p < 0.01$).

Thus, when 0-ending became less important for transaction convenience, their share decreased, but it stayed high at stores both with and without tills. It is another indication that although transaction convenience played some role in the high share of 0-ending prices, it is not the only reason.

In column 2 of Table A3, we test whether the rigidity of 0-ending prices changed after January 2008 at convenience stores with and without tills. To do so, we add to the regression a dummy for the period following January 2008, and its interactions with 0-ending prices, 9-ending prices, transaction inconvenience, and stores without tills.

We find that before 2008, 0-ending prices were more rigid than other prices at convenience stores ($\beta = -0.056, p < 0.01$). We also find no statistically significant differences in the rigidity of 0-ending prices at convenience stores with and without a till ($\beta = -0.062, p > 0.55$).

After 2008, we find that 0-ending prices became more rigid at convenience stores with a till than before 2008 ($\beta = -0.023, p < 0.01$). The difference between stores with and without tills is not statistically significant ($\beta = 0.164, p > 0.10$). Thus, after 2008, 0-ending prices were more rigid than before 2008 at convenience stores with a till, and as rigid as they were before 2008 at convenience stores without a till ($F = 2.0, p > 0.15$).

In summary, our results suggest that convenience played some role in the use of 0-ending prices at convenience stores. Convenience stores where the retailers had a greater incentive to use 0-ending prices to reduce computation effort and time used more 0-ending prices than stores that had less incentive to do so. Nevertheless, the share of 0-ending prices was over 60% also in stores that had little incentive to use 0-ending prices for reducing the computation effort. We, therefore, conclude that computation effort was not the only reason for using 0-ending prices, and perhaps not the most important also.

Table A1. Probability of a price change at convenience stores and superstores, Israel

	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	(8)
0-Ending	0.010*** (0.000)	0.089*** (0.001)	0.002*** (0.000)	0.008*** (0.000)	0.001 (0.002)	−0.056*** (0.000)	−0.044*** (0.002)	−0.132*** (0.010)
9-Ending	−0.045*** (0.000)	−0.038*** (0.001)	−0.054*** (0.000)	−0.047*** (0.000)	−0.201*** (0.002)	−0.018*** (0.000)	−0.110*** (0.002)	−0.141*** (0.012)
Transaction-Inconvenience	0.017*** (0.000)	0.022*** (0.000)		0.009*** (0.000)	0.035*** (0.000)	0.014*** (0.000)	0.001*** (0.000)	−0.013*** (0.000)
Convenience Store	−0.043*** (0.000)	−0.050*** (0.001)	−0.037*** (0.000)	−0.053*** (0.000)	−0.234*** (0.000)			
Convenience× 0-Ending	−0.063*** (0.000)	−0.113*** (0.002)	−0.071*** (0.000)	−0.053*** (0.000)	−0.218*** (0.000)			
Convenience× 9-Ending	0.030*** (0.000)	0.003*** (0.001)	0.018*** (0.000)	0.036*** (0.000)	0.121*** (0.000)			
Convenience× Transaction-Inconvenience	−0.003*** (0.000)	−0.025*** (0.000)		0.001*** (0.000)	0.005*** (0.000)			
Price Level	0.001*** (0.000)	0.012*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.020*** (0.000)
Log of the Population	0.005*** (0.000)	0.012*** (0.000)	0.010*** (0.000)	0.005*** (0.000)	0.015*** (0.000)	0.005*** (0.000)	−0.016*** (0.000)	0.014*** (0.001)
Socio-Economic Score	−0.004*** (0.000)	−0.006*** (0.000)	−0.003*** (0.000)	−0.003*** (0.000)	−0.013*** (0.000)	−0.003*** (0.000)	−0.009*** (0.000)	0.002*** (0.000)
Share of Women	0.034*** (0.000)	0.022*** (0.000)	0.083*** (0.000)	0.032*** (0.000)	0.112*** (0.000)	0.034*** (0.002)	1.159 (0.839)	−10.803 (165.526)
Log of the Distance from Tel-Aviv (in km)	−0.007*** (0.000)	−0.014*** (0.000)	−0.011*** (0.000)	−0.008*** (0.000)	−0.033*** (0.000)	−0.005*** (0.000)	−0.013*** (0.000)	−0.070*** (0.001)
Share of Minority Groups	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.000*** (0.000)	0.001*** (0.000)	0.001*** (0.000)
Sale Dummy	0.440*** (0.000)	0.373*** (0.000)	0.534*** (0.000)		4.351*** (0.081)			
2-Ending						0.014*** (0.000)	0.024*** (0.002)	
3-Ending						0.041*** (0.000)	−0.011*** (0.003)	
4-Ending						0.033*** (0.000)	0.035*** (0.003)	
5-Ending						−0.007*** (0.000)	−0.090*** (0.002)	
6-Ending						−0.006*** (0.000)	−0.032*** (0.002)	
7-Ending						−0.009*** (0.000)	−0.084*** (0.002)	
8-Ending						0.026*** (0.000)	0.002** (0.001)	
Constant	0.181*** (0.006)	−0.16 (0.012)	0.152*** (0.008)	0.215*** (0.005)	−0.683*** (0.064)	0.128*** (0.006)	0.079 (0.196)	5.750 (40.593)
R^2	0.341	0.255	0.323	0.282		0.341	0.136	0.056
χ^2					50,415.7			
Number of Observations	527,633	130,505	85,837	514,682	564,742	442,811	121,931	3,585

Notes: The table presents the results of estimating regressions of the probability of a price change. Columns 1–4 and 6–8 report the results of estimating linear probability regressions. Column 5 reports the results of estimating a probit regression. The independent variable in all regressions is a dummy that equals 1 if the price has changed in a given month. The independent variables are: 0-Ending – a dummy for 0 ending prices, 9-Ending – a dummy for 9-ending prices, Transaction-Inconvenience – the minimum number of coins necessary for paying a price in cash, Convenience Store – an store that is defined as a convenience store/store, Price Level – the price in month $t – 1$ rounded to the nearest NIS, Log of the Population – the log of the number of inhabitants in the town where the store is located, Socio-Economic Score – the socio-economic score of the town where the store is located, as reported by the Israel's Central Bureau of Statistics (CBS), Share of Women – the share of women in the town where the store is located, Log of the Distance from Tel-Aviv (in km) – the log of the distance of the town where the store is located from Tel-Aviv, Share of Minority Groups – the share of minority groups in the town where the store is located, Sale Dummy – a dummy for sale prices in month $t – 1$, 2-Ending − a dummy, which equals 1 if the previous price was 2-ending, 3-Ending − a dummy, which equals 1 if the previous price was 3-ending, 4-Ending − a dummy, which equals 1 if the previous price was 4-ending, 5-Ending − a dummy, which equals 1 if the previous price was 5-ending, 6-Ending − a dummy, which equals 1 if the previous price was 6-ending, 7-Ending − a dummy, which equals 1 if the previous price was 7-ending, 8-Ending − a dummy, which equals 1 if the previous price was 8-ending. All regressions also include controls for product categories, the six regions of Israel, and the quarter in which the observation was taken. Column 1 includes observations on prices ≤ 200 NIS. Column 2 includes observations on prices ≤ 4 NIS. Column 3 includes observations on prices that can be paid using a single coin or a single note. Column 4 includes observations on regular prices. Column 5 includes all observations. Column 6 includes all observations from convenience stores. Column 7 includes all observations from superstores. Column 8 reports the results of estimating the regression using observations only from stores that the CBS flags as convenience stores. Standard errors are clustered at the level of the store where the observation was taken. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Table A2. Testing the significance of the coefficient of 0-endings vs. other endings

0-Ending vs.	In Convenience Stores	In Superstores
1-Ending	58.71***	1.22
2-Ending	46.50***	3.83*
3-Ending	71.31***	0.88
4-Ending	106.05***	3.45*
5-Ending	24.87***	9.55***
6-Ending	19.07***	0.19
7-Ending	23.64***	2.08
8-Ending	74.41***	2.92*
9-Ending	31.22***	26.52***

Note: The figures in the table are the *F* test statistic values for comparing the coefficient of 0-ending prices with the coefficients of 1-ending, 2-ending… 9-ending prices, based on the results of the regressions reported in columns 6 and 7 of Table A1. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Table A3. Price rigidity at stores with and without a till

	(1)	(2)
0-Ending	-0.062*** (0.007)	-0.056*** (0.008)
9-Ending	-0.035*** (0.012)	-0.011 (0.015)
Transaction-Inconvenience	0.012*** (0.002)	0.014*** (0.002)
Stores with no-till dummy	0.040 (0.081)	0.073 (0.104)
Stores with no-till dummy × 0-Ending	-0.026 (0.080)	-0.062 (0.103)
Stores with no-till dummy × 9-Ending	-0.070 (0.081)	-0.113 (0.104)
Stores with no-till dummy × Transaction-Inconvenience	0.010*** (0.003)	0.012*** (0.004)
Price Level	0.000*** (0.000)	0.000*** (0.000)
Log of the Population	0.004 (0.005)	0.004 (0.005)
Socio-Economic Score	-0.003 (0.002)	-0.003 (0.002)
Share of Women	0.027 (0.040)	0.026 (0.039)
Log of the Distance from Tel-Aviv (in km)	-0.004 (0.007)	-0.004 (0.007)
Share of Minority Groups	-0.000 (0.000)	-0.000 (0.000)
Sale dummy	0.396*** (0.008)	0.396*** (0.008)
Post-2008 dummy		0.001 (0.016)
Post-2008 dummy × 0-ending		-0.023** (0.008)
Post-2008 dummy × 9-ending		-0.044*** (0.010)
Post-2008 dummy × Transaction inconvenience		-0.004*** (0.001)
Post-2008 dummy × Stores with no-till dummy		-0.147 (0.099)
Post-2008 dummy × Stores with no-till dummy × 0-ending		0.164 (0.100)
Post-2008 dummy × Stores with no-till dummy × 9-ending		0.169* (0.101)
Post-2008 dummy × Stores with no-till dummy × Transaction inconvenience		-0.008** (0.004)
Constant	0.146** (0.073)	0.141** (0.074)
R^2	0.343	0.387
Number of Observations	442,811	442,811

Notes: The table presents the results of estimating regressions of the probability of a price change. The independent variable in all regressions is a dummy that equals 1 if the price has changed in a given month. The independent variables are: 0-Ending – a dummy for 0 ending prices, 9-Ending – a dummy for 9-ending prices, Transaction-Inconvenience – the minimum number of coins necessary for paying a price in cash, Stores with no-till dummy – A dummy that equals 1 if the store is either an open market stall or a kiosk, Price Level – the price in month t – 1 rounded to the nearest NIS, Log of the Population – the log of the number of inhabitants in the town where the store is located, Socioeconomic Score – the socioeconomic score of the town where the store is located, as reported by the Israel's Central Bureau of Statistics (CBS), Share of Women – the share of women in the town where the store is located, Log of the Distance from Tel-Aviv (in km) – the log of the distance of the town where the store is located from Tel-Aviv, Share of Minority Groups – the share of minority groups in the town where the store is located, Sale Dummy – a dummy for sale prices in month $t - 1$, post-2008 dummy – a dummy that equal 1 for observations after January 2008. Standard errors are clustered at the level of the store where the observation was taken. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Appendix B. Robustness tests with Dominick's data: estimating price rigidity

In the paper, we report that for the goods in the front-end-candies category at Dominick's, 0-ending prices are common and relatively rigid. Below, we show that this phenomenon is unique to the front-end-candies category: in other product categories at Dominick's, 0-endings are not particularly common or rigid.

Figure B1 depicts the distribution of the price endings in each of the 29 product categories at Dominick's. Table B1 complements it by showing the share of 0-ending prices in each category. It also provides the results of a Wilcoxon rank-sum test for comparing the share of 0-ending prices in the front-end-candies category with the shares in each of the other 28 categories.

Table B1 shows that the share of 0-ending prices in the front-end-candies category, 24.15 percent, is exceptionally high for Dominick's. The category with the next highest share of 0-ending prices is frozen dinners, with 13.12 percent. Thus, the share of 0-ending prices in the front-end-candies category is 84 percent higher than the share of 0-ending prices in the category with the next highest share of 0-ending prices, and more than 5 times the cross-category average of 4.74 percent.

Table B2 reports the results of estimating regressions of the likelihood of price changes in each of Dominick's 29 product categories. These regressions are equivalent to the regressions reported in Column 2 of Table 4 in the paper. The dependent variable is a dummy that equals 1 if the price has changed, and 0 otherwise. The independent variables include a dummy for 0-ending prices, a dummy for 9-ending prices, a transaction-inconvenience score that equals the minimum number of coins needed for paying the price, a dummy for quarter-multiple that equals 1 if the price ends in 25 or 75, the price level, calculated as the previous price rounded to the nearest dollar, the absolute value of changes in the wholesale price, and a dummy for sale prices, based on a 4-week sales filter.[4] The regression also includes sub-cateogries×stores×weeks fixed effects. We cluster the standard errors at the sub-categories×stores×weeks level.

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[4] We exclude outlier observations, which we define conservatively as a change in the wholesale price in excess of 150 percent. This results in dropping 578,198 observations, which comprise about 0.6% of the total number of observations.

To save space, we report only the coefficients of the main variables of interest: The 0-ending price dummy, the 9-ending price dummy, the quarter-multiple dummy, and the transaction-inconvenience index. From the table, we can see that in all 29 categories, 9-ending prices are more rigid than other prices. The coefficient of 0-ending prices, however, is negative in only 5 product categories: front-end candies, frozen entrees, grooming products, soft drinks, and toothbrushes.

Table B3 reports the results of the same regressions, except that now we restrict the sample to regular prices only by removing sale and bounce-back prices, based on a 4-week sales filter. Similar to the above, 9-ending prices are more rigid than other prices in all 29 product categories. 0-ending prices, however, are more rigid than other prices in only 2 product categories: front-end-candies and toothbrushes.

The results of these analyses, therefore, do not support the hypothesis that 0-endings are used as a signal of quality, because then 0-ending prices would be more rigid than other prices in other categories as well (Stiving 2000).

Thus, neither the popularity nor the rigidity of 0-ending prices is common at Dominick's stores. We believe that the special nature of the front-end-candies category, where shoppers make spontaneous decisions after considering perhaps only 1 or 2 products, can explain why 0-ending prices are both common and rigid in this category.

Table B4 contains the results of several robustness tests of the results we report in the paper for the front-end-candies category. In column 1 we use the same specification as in Tables B2 and B3. However, here we use all observations, including those with wholesale price changes of over 150%. Including these outlier observations, reduces the effect of the wholesale price changes ($\beta = 0.000, p < 0.01$), but the effect of 0-ending prices remains negative ($\beta = -0.094, p < 0.01$).

In column 2 we use Dominick's sale price indicator rather than our sales filter to identify sales. As Peltzman (2000) notes, Dominick's sales indicator was not set on a regular basis and, consequently, it is unreliable. Nevertheless, when we use it for testing the robustness of our results, we find that the coefficient of 0-ending prices is negative and significant ($\beta = -0.146, p < 0.01$).

In column 3 we restrict the data to observations on regular prices by removing observations on sale and bounce-back prices, using Dominick's sale indicator. We find that 0-ending prices are more rigid than other prices in this sample as well ($\beta = -0.114, p < 0.01$).

In column 4, we restrict the sample to sale prices only, again using Dominick's sales indicator. The coefficient of 0-ending prices is positive and significant ($\beta = 0.016, p < 0.05$). We also find that 9-ending ($\beta = 0.142, p < 0.01$) and 5-ending prices ($\beta = 0.235, p < 0.01$) are more likely to change than other prices. Thus, when we look at sale prices, it does not seem that the price ending affects the price rigidity. However, these results must be interpreted with caution, because as noted above, Dominick's sale indicator was not set on a regular basis. Consequently, many sale prices are not accounted for in this regression.

In column 5, we add dummy variables for each possible ending, using the ending of 1 as a control. We find that the prices that are the most rigid are those that end with 9, 5, and 0. In other words, the most rigid prices are those that end with either 9, or the prices with "round" endings (i.e., 0 and 5). In Table B5, we show that the differences between the coefficient of 0-ending prices and the coefficients of the prices with other endings are statistically significant. These results confirm that 0, 9, and 5 are the most rigid endings in Dominick's front-end candies category.

In column 6, we use only the data points where the price was the same over two subsequent observations. Our data comes from scanner data, and therefore, prices are calculated as revenue over quantity sold. Thus, there is a chance that some price changes in the dataset are due to the method by which prices are calculated (Strulov-Shlain, 2019, Cambell and Eden, 2014). We may get a "spurious" price change, for example, if some transactions were not properly recorded, or if some consumers used bonus coupons. By removing prices that last only one week, we reduce the risk that such measurement errors affect our results because it is unlikely that there will be measurement errors two weeks in a row that give the same price (Strulov-Shlain, 2019). The results show that after excluding all the prices that lasted only one week, 0-ending prices are still more rigid than other prices ($\beta = -0.153, p < 0.01$).

Thus, including all observations, using Dominick's sales indicator instead of a sales filter, or removing observations on prices that last one week, does not change the results we report in the paper. In the front-end-candies category, 0-ending prices are more rigid than other prices regardless of whether they are regular or sale prices.

As a final robustness check, we examine if our results hold when we include data from before January 1991. In the paper, we remove data collected before 1991 because, in the earlier part of the data, Dominick's participated in a pricing experiment in cooperation with the faculty of the Booth School of Business at the University of Chicago, and this might have affected the outcomes. Table B6 gives the results when we use the full set of data.

In column 1, the only independent variables are the 0-ending dummy, the 9-ending dummy, and the transaction-inconvenience score. We find that 0-endings ($\beta = -0.018, p < 0.01$) and 9-endings ($\beta = -0.135, p < 0.00$) reduce the likelihood of a price change. An increase in the transaction-inconvenience score increases the likelihood of a price change ($\beta = 0.041, p < 0.01$).

In column 2, we add the following controls: a dummy for quarter-multiple, the price level, the absolute value of changes in the wholesale price, and a dummy for sale prices, all defined as above.[5] The regression also includes sub-cateogries×stores×weeks fixed effects.

We find that the effects of 0-ending prices ($\beta = -0.137, p < 0.01$) and 9-ending prices ($\beta = -0.166, p < 0.01$) remain negative and statistically significant. The effect of the transaction-inconvenience score is still positive and statistically significant ($\beta = 0.016, p < 0.01$).

Thus, using the full dataset does not change any of our main results. 0-ending prices, as well as 9-ending prices, are more rigid than other ending prices.

[5] We exclude outlier observations, which we define conservatively as a change in the wholesale price in excess of 150 percent. When we use the full set of data, this results in dropping 66,232 observations, about 1.5% of the total number of observations.

Figure B1. Frequency distribution of the last digit of the retail prices at Dominick's, by product category, September 14, 1989–May 8, 1997

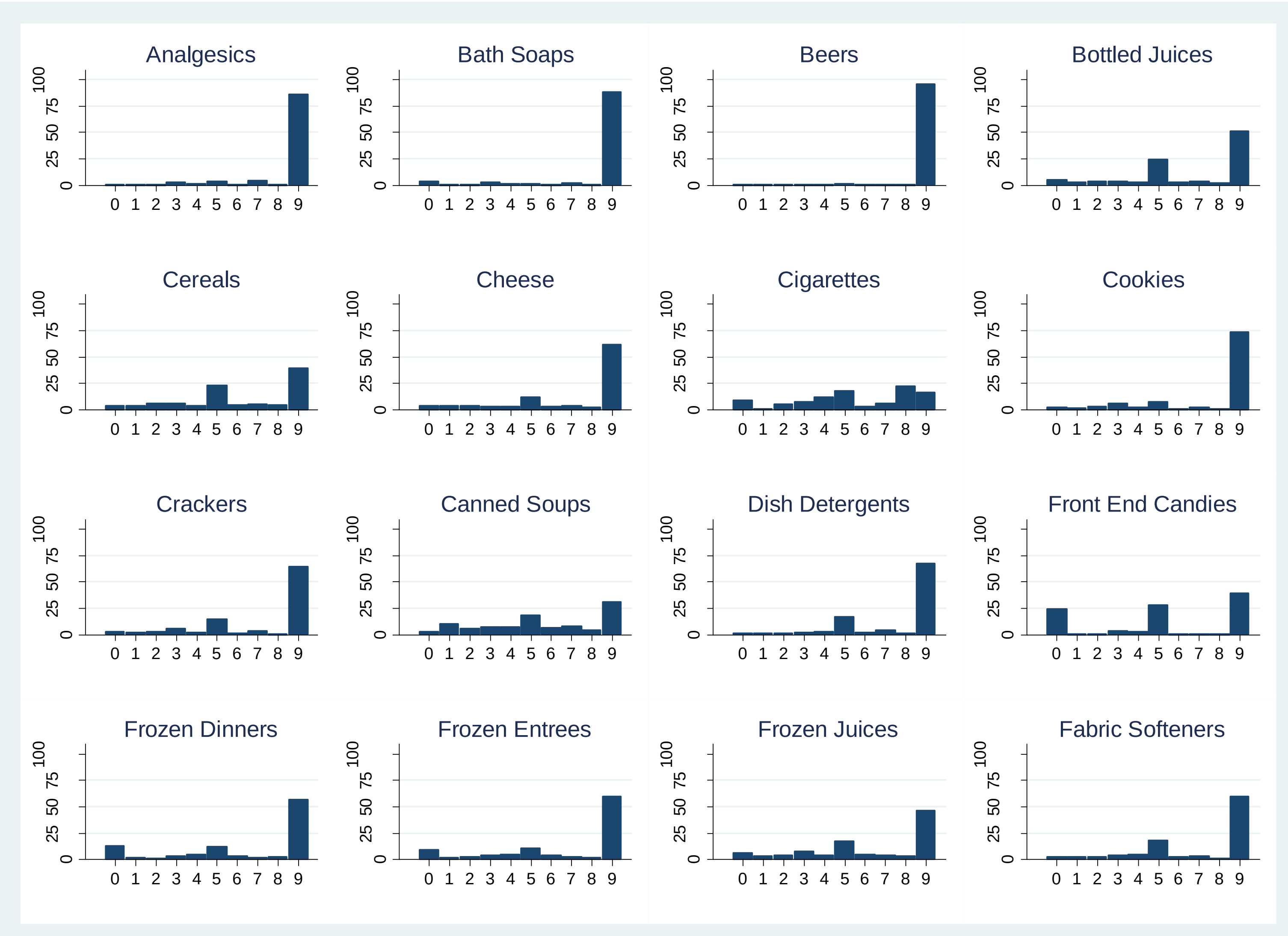


Figure B1. Frequency distribution of the last digit of the retail prices at Dominick's, by product categories, September 14, 1989–May 8, 1997 (Cont.)

Table B1. Percentage of 0-ending prices at Dominick's, by product categories

Product Category	**% 0-Ending Prices**	**No. of Observations**	**Wilcoxon Rank-Sum Test**
Analgesics	0.39	3,040,172	906.61***
Bath Soaps	3.07	418,097	312.79***
Beers	0.39	1,966,148	740.85***
Bottled Juices	4.84	4,325,024	808.72***
Canned Soups	2.77	5,504,494	1023.43***
Cereals	4.12	4,707,776	876.66***
Cheese	4.15	6,752,328	1014.52***
Cigarettes	8.69	1,801,470	440.12***
Cookies	2.14	7,568,429	1243.23***
Crackers	2.92	2,228,269	687.34***
Dish Detergents	1.21	2,164,793	742.81***
Fabric Softeners	2.81	2,278,995	698.42***
Front-End-Candies	24.15	4,437,054	N/A
Frozen Dinners	13.12	1,654,053	296.33***
Frozen Entrees	9.32	7,172,075	687.77***
Frozen Juices	6.52	2,368,157	570.00***
Grooming Products	3.37	4,065,694	866.49***
Laundry Detergents	1.25	3,277,445	895.12***
Oatmeal	2.23	981,037	489.39***
Paper Towels	2.73	940,757	468.26***
Refrigerated Juices	3.28	2,166,755	665.55***
Shampoos	2.41	4,676,790	975.85***
Snack Crackers	2.88	3,487,565	837.26***
Soaps	2.06	1,835,196	659.75***
Soft Drinks	4.25	10,741,743	1231.64***
Toilet Papers	4.20	1,149,973	476.27***
Toothbrushes	1.62	1,839,536	675.47***
Toothpastes	2.39	2,981,532	804.89***
Tuna	3.46	2,382,983	687.24***
Average or Total	4.74	98,914,340	

Notes: The table presents the percentage of 0-ending prices in each of Dominick's 29 product categories. The final column reports the results of the *z*-statistic for the Wilcoxon rank sum test for comparing the share of 0-ending prices in the front-end-candies category with the share of 0-ending prices in each of the other 28 product categories. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Table B2. Price rigidity of the products at Dominick's, by product categories, all observations

Category	Main Independent Variable				
	0-Ending Price	**9-Ending Price**	**Quarter-Multiple Price**	**Transaction-Inconvenience**	***N***
Analgesics	0.226*** (0.001)	−0.098*** (0.000)	−0.056*** (0.001)	−0.007*** (0.000)	2,997,267
Bath Soaps	0.068*** (0.004)	−0.226*** (0.001)	0.063*** (0.000)	−0.005*** (0.000)	402,600
Beers	0.116*** (0.001)	−0.500*** (0.000)	−0.426*** (0.000)	0.011*** (0.000)	1,936,341
Bottled Juices	0.159*** (0.000)	−0.066*** (0.000)	−0.016*** (0.000)	0.015*** (0.000)	4,276,615
Canned Soups	0.183*** (0.000)	−0.026*** (0.000)	−0.027*** (0.000)	0.005*** (0.000)	5,450,234
Cereals	0.080*** (0.000)	−0.027*** (0.000)	−0.014*** (0.000)	−0.001*** (0.000)	4,661,586
Cheese	0.141*** (0.000)	−0.186*** (0.000)	−0.073*** (0.001)	0.012*** (0.000)	6,696,191
Cigarettes	0.040*** (0.000)	−0.014*** (0.000)	−0.001*** (0.000)	0.009*** (0.000)	1,762,231
Cookies	0.122*** (0.000)	−0.168*** (0.000)	−0.008*** (0.000)	0.012*** (0.000)	7,471,949
Crackers	0.120*** (0.000)	−0.174*** (0.000)	−0.016*** (0.001)	0.010*** (0.000)	2,203,563
Dish Detergents	0.432*** (0.002)	−0.060*** (0.000)	−0.006*** (0.000)	0.007*** (0.000)	2,141,470
Fabric Softeners	0.115*** (0.002)	−0.046*** (0.000)	−0.059*** (0.000)	−0.001*** (0.000)	2,252,077
Front End Candies	−0.013*** (0.001)	−0.079*** (0.000)	0.031*** (0.000)	0.039*** (0.000)	4,437,054
Frozen Dinners	0.074*** (0.004)	−0.249*** (0.000)	−0.148*** (0.002)	0.006*** (0.000)	1,623,448
Frozen Entrees	−0.014*** (0.001)	−0.176*** (0.000)	−0.026*** (0.001)	0.017*** (0.000)	6,997,451
Frozen Juices	0.010*** (0.000)	−0.017*** (0.000)	−0.013*** (0.000)	−0.002*** (0.000)	2,339,853
Grooming Products	−0.015*** (0.003)	−0.245*** (0.000)	0.098*** (0.000)	−0.002*** (0.000)	3,974,487
Laundry Detergents	0.153*** (0.001)	−0.084*** (0.000)	−0.070*** (0.000)	−0.010*** (0.000)	3,230,290
Oatmeal	0.158*** (0.001)	−0.069*** (0.000)	−0.025*** (0.000)	−0.002*** (0.000)	970,697
Paper Towels	0.179*** (0.002)	−0.020*** (0.001)	0.073*** (0.004)	0.021*** (0.000)	924,672
Refrigerated Juices	0.267*** (0.000)	−0.116*** (0.000)	−0.160*** (0.002)	−0.005*** (0.000)	2,146,335
Shampoos	0.179*** (0.002)	−0.244*** (0.001)	−0.058*** (0.002)	−0.010*** (0.000)	4,529,320
Snack Crackers	0.003*** (0.000)	−0.096*** (0.000)	−0.159*** (0.000)	0.006*** (0.000)	2,479,891
Soaps	0.271*** (0.001)	−0.107*** (0.000)	−0.012*** (0.001)	0.004*** (0.000)	1,807,790
Soft Drinks	−0.008*** (0.002)	−0.286*** (0.001)	−0.139*** (0.005)	−0.004*** (0.000)	10,376,206

Toilet Papers	0.256*** (0.002)	−0.046*** (0.000)	−0.057*** (0.001)	−0.004*** (0.000)	1,134,801
Toothbrushes	−0.009*** (0.002)	−0.082*** (0.001)	−0.002*** (0.000)	−0.022*** (0.000)	1,805,772
Toothpastes	0.091*** (0.002)	−0.027*** (0.000)	0.158*** (0.002)	−0.022*** (0.000)	2,939,561
Tuna	0.073*** (0.001)	−0.077*** (0.000)	−0.019*** (0.000)	0.006*** (0.000)	2,358,245

Notes: The table presents the results of linear probability model regressions of the probability of a price change. The dependent variable is a dummy which equals 1 if the price of good *i* at store *j* changed on week *t*. The independent variables are 0-Ending − a dummy which equals 1 if the previous price was 0-ending, 9-Ending − a dummy which equals 1 if the previous price was 9-ending, Quarter-multiple − a dummy which equals 1 if the previous price ended in a multiple of a quarter (coin), and Transaction-Inconvenience Score – the minimum number of coins needed to pay the previous price. The regressions also include the following variables: Price Level – the previous price rounded to the nearest dollar, Sale Price – a dummy for the previous price being a sale price, and Absolute Value of the Percentage Change in the Wholesale Price – the absolute percentage change in the wholesale price. The regressions also include products×stores fixed effects. We exclude outlier observations, which we define as a change in the wholesale price over 100 percent. This results in dropping 578,198 observations, about 0.6% of the total. Robust standard errors, clustered at the store-product level, are reported in parentheses. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Table B3. Price rigidity of the products at Dominick's, by product categories, regular prices

Category	Main Independent Variable				
	0-Ending Price	**9-Ending Price**	**Quarter-Multiple Price**	**Transaction-Inconvenience**	***N***
Analgesics	0.223*** (0.000)	−0.099*** (0.000)	−0.056*** (0.000)	−0.006*** (0.000)	2,821,654
Bath Soaps	0.053*** (0.000)	−0.216*** (0.000)	0.137*** (0.000)	0.002*** (0.000)	382,932
Beers	0.123*** (0.000)	−0.536*** (0.000)	−0.424*** (0.000)	0.015*** (0.000)	1,495,058
Bottled Juices	0.146*** (0.000)	−0.098*** (0.000)	−0.020*** (0.000)	0.024*** (0.000)	3,455,004
Canned Soups	0.162*** (0.000)	−0.037*** (0.000)	−0.036*** (0.000)	0.006*** (0.000)	4,730,051
Cereals	0.053*** (0.000)	−0.037*** (0.000)	−0.014*** (0.000)	0.004*** (0.000)	4,161,630
Cheese	0.149*** (0.000)	−0.176*** (0.000)	−0.063*** (0.000)	0.013*** (0.000)	5,129,546
Cigarettes	0.048*** (0.000)	−0.020*** (0.000)	0.000*** (0.000)	0.012*** (0.000)	1,750,716
Cookies	0.173*** (0.000)	−0.176*** (0.000)	−0.049*** (0.000)	0.016*** (0.000)	6,269,874
Crackers	0.145*** (0.000)	−0.168*** (0.000)	−0.061*** (0.000)	0.015*** (0.000)	1,794,652
Dish Detergents	0.411*** (0.000)	−0.081*** (0.000)	−0.022*** (0.000)	0.009*** (0.000)	1,850,794
Fabric Softeners	0.094*** (0.000)	−0.074*** (0.000)	−0.061*** (0.000)	0.006*** (0.000)	1,987,360
Front End Candies	−0.005*** (0.000)	−0.056*** (0.000)	0.017*** (0.000)	0.030*** (0.000)	4,008,259
Frozen Dinners	0.057*** (0.000)	−0.277*** (0.000)	−0.213*** (0.000)	0.013*** (0.000)	1,212,996
Frozen Entrees	0.013*** (0.000)	−0.150 (0.000)	−0.044*** (0.000)	0.017*** (0.000)	5,616,611
Frozen Juices	0.017*** (0.000)	−0.048*** (0.000)	−0.005*** (0.000)	0.003*** (0.000)	1,806,969
Grooming Products	0.019*** (0.000)	−0.247*** (0.000)	0.084*** (0.000)	0.001*** (0.000)	3,569,479
Laundry Detergents	0.133*** (0.000)	−0.101*** (0.000)	−0.057*** (0.000)	−0.005*** (0.000)	2,816,612
Oatmeal	0.192*** (0.000)	−0.072*** (0.000)	−0.020*** (0.000)	0.009*** (0.000)	847,425
Paper Towels	0.175*** (0.000)	−0.051*** (0.000)	0.024*** (0.000)	0.020*** (0.000)	722,957
Refrigerated Juices	0.295*** (0.000)	−0.150*** (0.000)	−0.119*** (0.000)	0.010*** (0.000)	1,459,298
Shampoos	0.135*** (0.000)	−0.258*** (0.000)	−0.026*** (0.000)	−0.005*** (0.000)	4,122,264
Snack Crackers	0.001 (0.006)	−0.096*** (0.002)	−0.159*** (0.006)	0.005*** (0.001)	2,468,519
Soaps	0.273*** (0.000)	−0.118*** (0.000)	−0.040*** (0.000)	0.006*** (0.000)	1,555,553
Soft Drinks	0.049*** (0.000)	−0.394*** (0.000)	−0.195*** (0.000)	−0.004*** (0.000)	6,807,239

Toilet Papers	0.198*** (0.000)	−0.089*** (0.000)	−0.075*** (0.000)	0.000*** (0.000)	880,326
Toothbrushes	−0.031*** (0.000)	−0.084*** (0.000)	−0.002*** (0.000)	−0.022*** (0.000)	1,625,533
Toothpastes	0.116*** (0.000)	−0.050*** (0.0000	0.165*** (0.000)	−0.018*** (0.000)	2,506,048
Tuna	0.108*** (0.000)	−0.083*** (0.000)	−0.018*** (0.000)	0.012*** (0.000)	2,081,953

Notes: The table presents the results of the estimation of a linear probability model regressions of the probability of a *regular* price change. To focus on regular prices, we exclude the observations on sale prices and bounce-back prices, using a 4-week sale filter to identify sale prices. The dependent variable is a dummy which equals 1 if the price of good i at store j changed on week t. The independent variables are 0-Ending − a dummy which equals 1 if the previous price was 0-ending, 9-Ending − a dummy which equals 1 if the previous price was 9-ending, Quarter-multiple − a dummy which equals 1 if the previous price ended in a multiple of a quarter (coin), and Transaction-Inconvenience Score – the minimum number of coins needed to pay the previous price. The regressions also include the following variables: Price Level – the previous price rounded to the nearest dollar, Sale Price – a dummy for the previous price being a sale price, and Absolute Value of the Percentage Change in the Wholesale Price – the absolute percentage change in the wholesale price. The regressions also include products×stores fixed effects. We exclude outlier observations, which we define as a change in the wholesale price over 100 percent. This results in dropping 578,198 observations, about 0.6% of the total. Robust standard errors, clustered at the store-product level, are reported in parentheses. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Table B4. Price rigidity of the products in the front-end-candies' category at Dominick's

	(1)	(2)	(3)	(4)	(5)	(6)
0-Ending	−0.094*** (0.003)	−0.146*** (0.003)	−0.114*** (0.004)	0.016** (0.008)	−0.0448*** (0.007)	−0.153*** (0.005)
9-Ending	−0.160*** (0.003)	−0.188*** (0.003)	−0.157*** (0.004)	0.142*** (0.006)	−0.487*** (0.007)	−0.163*** (0.004)
Transaction-Inconvenience Score	0.021*** (0.001)	0.019*** (0.001)	0.017*** (0.001)	0.004 (0.001)	0.022*** (0.001)	−0.008*** (0.0010
Quarter-multiple	−0.011*** (0.001)	−0.014*** (0.002)	0.020*** (0.001)	0.147*** (0.005)	−0.003** (0.001)	−0.030*** (0.001)
Price Level	−0.047*** (0.002)	−0.071*** (0.001)	−0.048*** (0.001)	0.047*** (0.004)	−0.040*** (0.002)	−0.010*** (0.010)
Absolute Value of the % Change in the Wholesale Price	0.000*** (0.000)	0.011*** (0.000)	0.009*** (0.000)	0.008*** (0.000)	0.011*** (0.000)	0.010*** (0.000)
5-Ending	−0.133*** (0.002)	−0.172*** (0.003)	−0.147*** (0.004)	0.235*** (0.004)	−0.466*** (0.006)	−0.161*** (0.004)
Sale Price (Sales Filter)	0.495*** (0.002)				0.391*** (0.003)	0.387*** (0.002)
Sale Price (Dominick's Sales Dummy)		0.263*** (0.003)				
2-Ending					−0.304*** (0.007)	
3-Ending					−0.428*** (0.008)	
4-Ending					−0.374*** (0.008)	
6-Ending					−0.122*** (0.009)	
7-Ending					−0.015* (0.009)	
8-Ending					−0.114*** (0.005)	
Constant	0.242*** (0.003)	0.226*** (0.003)	0.167*** (0.004)	0.310*** (0.006)	0.489*** (0.006)	0.204*** (0.006)
R^2	0.219	0.286	0.118	0.092	0.378	0.347
N	3,708,902	3,686,663	3,2143,57	327,180	3,686,663	3,483,539

Notes: The table presents the results of estimating a linear probability model regression of the probability of a price change. The dependent variable is a dummy, which equals 1 if the price of good *i* at store *j* changed on week *t*. The independent variables are: 0-Ending − a dummy which equals 1 if the previous price was 0-ending, 9-Ending − a dummy which equals 1 if the previous price was 9-ending, Quarter-multiple − a dummy which equals 1 if the previous price ended in 25 or 75, Transaction-Inconvenience Score – the minimum number of coins needed to pay the previous price, price level – the previous price rounded to the nearest dollar, Absolute Value of the Percentage Change in the Wholesale Price – the absolute percentage change in the wholesale price, Sale Price (Sales Filter) – a dummy for the previous price being a sale price based on a 4 week sale filter, Sale Price (Dominick's Sales Dummy) – a dummy for the previous price being a sale price, based on Dominick's sales indicator, 2-Ending − a dummy which equals 1 if the previous price was 2-ending, 3-Ending − a dummy which equals 1 if the previous price was 3-ending, 4-Ending − a dummy which equals 1 if the previous price was 4-ending, 5-Ending − a dummy which equals 1 if the previous price was 5-ending, 6-Ending − a dummy which equals 1 if the previous price was 6-ending, 7-Ending − a dummy which equals 1 if the previous price was 7-ending, and 8-Ending − a dummy which equals 1 if the previous price was 8-ending. The regressions also include products×stores fixed effects. The first and second columns contain all observations. In column 1, we estimate the regression using all observations, including those with changes in the wholesale price above 150%. In column 2, we estimate the regressions using Dominick's sales dummy instead of the sale filter to identify sales. In column 3, we estimate the regression using a sample of regular prices, by removing all observations that Dominick's sales dummy identifies as sale prices and the bounce-back prices. In column 4, we estimate the regression using a sample of sale prices, by including only the prices that Dominick's sales dummy identifies as sale prices. In column 5, we add dummy variables for each possible ending, using ending 1 as a control. In column 6, we use only the data points where the price was the same over two subsequent observations. Robust standard errors, clustered at the store-product level, are reported in parentheses. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Table B5. Testing the significance of the coefficient of 0-ending vs. other endings

0-Ending vs.	**Test-statistic**
1-Ending	4658.3***
2-Ending	636.5***
3-Ending	89.1***
4-Ending	430.9***
5-Ending	475.6***
6-Ending	7693.7***
7-Ending	10773.0***
8-Ending	2741.2***
9-Ending	1055.8***

Note: The figures in the table are the F test statistic values for comparing the coefficient of 0-ending prices with the coefficients of 1-ending, 2-ending, …, and 9-ending prices, based on the results of the regressions reported in column 5 of Table F4. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Table B6. Price rigidity of the products in the front-end-candies category at Dominick's, a full dataset with all observations

	(1)	**(2)**
0-Ending	-0.018*** (0.001)	-0.137*** (0.003)
9-Ending	-0.135*** (0.002)	-0.166*** (0.003)
Transaction-Inconvenience Score	0.041*** (0.001)	0.016*** (0.001)
Quarter-multiple		-0.008*** (0.001)
Price Level		-0.040*** (0.001)
Absolute Value of the % Change in the Wholesale Price		0.012*** (0.000)
5-Ending		-0.151*** (0.002)
Sale Price (Sales Filter)		0.416*** (0.003)
Constant	0.075*** (0.002)	0.185*** (0.002)
R^2	0.031	0.361
N	4,402,665	4,402,665

Notes: The table presents the results of estimating a linear probability model regression of the probability of a price change. The dependent variable is a dummy, which equals 1 if the price of good *i* at store *j* changed on week *t*. The independent variables are 0-Ending − a dummy which equals 1 if the previous price was 0-ending, 9-Ending − a dummy which equals 1 if the previous price was 9-ending, Quarter-multiple − a dummy which equals 1 if the previous price ended in 25 or 75, Transaction-Inconvenience Score – the minimum number of coins needed to pay the previous price, price level – the previous price rounded to the nearest dollar, Absolute Value of the Percentage Change in the Wholesale Price – the absolute percentage change in the wholesale price, Sale Price (Sales Filter) – a dummy for the previous price being a sale price based on a 4-week sale filter. The regressions also include sub-categories×stores×weeks fixed effects. The regressions use the full set of data, including observations from before 1991. Robust standard errors, clustered at the store-product level, are reported in parentheses.
* $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Appendix C. Robustness tests with Dominick's data: **estimating demand**

Table C1 contains the results of several robustness tests for the estimation of demand equations for front-end-candies. In panel 1 of Table 3 in the paper, we report the estimation results of regressions of the product-level demand equations: the dependent variable is the log of the quantity of product *q* sold at store *s*, in week *t*. The independent variables include dummies for 0- and 9-ending prices, the transaction-inconvenience score, the log of the price, the log of the average price of other products in the same sub-category, a dummy for sale prices, the quantity sold in store *s* in week *t* – 1, and fixed effects of stores, years, and months. We add the average price of other products in the same subcategory as a control for competition. We add the year and month fixed effects to control for possible seasonality in demand (Butters et al., 2020). We also add fixed effects for holidays, which include Christmas, New Year, Presidents' Day, Easter, Memorial Day, 4th of July, Labor Day, Halloween, and Thanksgiving. To minimize the effect of endogeneity, we use the log of the average price in other stores as an instrument for the price.

In panel A, we report the results when we remove the control for the quantity sold in store *s* in week *t* – 1. This has little effect on the coefficients of 0- and 9-ending prices. The mean effect of 0-endings is positive ($\bar{\beta} = 0.202$) and a large majority of the coefficients are positive: 55 are positive vs. 25 negative. The mean effect of 9-endings is negative ($\bar{\beta} = -0.014$), and a minority of the coefficients is positive: 32/80 coefficients are positive.

In the paper, we use the average price in other stores as an instrument. This might not be ideal, because all the stores are located in one city, Chicago. Therefore, in panel B, we use the wholesale prices as an instrument for the price. We find that the mean effect of 0-endings is positive ($\bar{\beta} = 0.135$). The mean effect of 9-ending is negative ($\bar{\beta} = -0.034$). Again, the majority of the 0-ending coefficients are positive (57/80), while a minority of the 9-ending coefficients are positive (31/80).

In the paper, we do not use observations collected before January 1991 because data from the earlier period could have been contaminated by pricing experiments that Dominick's conducted. As a test of robustness, therefore, we estimate the regressions using the full set of data. The results are reported in panel C.

Table C1. Regressions of the effects of price endings on demand in the front-end-candies category: Dominick's, U.S.

	Average	Quantity-adjusted average	Revenue-adjusted average	Num. of positive coefficients	Num. of Negative coefficients	Num. of positive and significant coefficients	Num. of negative and significant coefficients	No. of observations
	Panel A							
0-ending price	0.202	0.246	0.220	55	25	42	12	1,988,759
9-ending price	-0.014	-0.038	-0.030	32	45	26	39	
Transaction-inconvenience score	0.084	0.094	0.081	66	14	53	10	
Log(price)	-0.258	-0.299	-0.378	20	60	15	55	
	Panel B							
0-ending price	0.135	0.133	0.115	57	23	38	13	1,987,194
9-ending price	-0.034	-0.065	-0.053	31	46	25	39	
Transaction-inconvenience score	0.066	0.074	0.069	68	12	60	9	
Log(price)	0.031	0.069	0.036	54	26	41	16	
	Panel C							
0-ending price	0.138	0.137	0.127	55	25	40	11	2,307,850
9-ending price	-0.062	-0.085	-0.068	28	49	18	40	
Transaction-inconvenience score	0.065	0.074	0.069	63	17	50	14	
Log(price)	-0.109	-0.110	-0.214	42	38	37	33	

Notes: The table summarizes the estimation results of reduced form product-level demand equations for 80 products in Dominick's front-end-candies category, a total of 80 regressions. In each regression, the dependent variable is the log of the quantity of product q sold at store s, in week t. The independent variables include a dummy for a 0-ending price (1 if the price ends with 0), a dummy for 9-ending prices (1 if the price ends with 9), the transaction-inconvenience score (the minimum number of coins needed to pay the previous price), the log of the price, the log of the average price of other products in the same sub-category, the quantity sold in the same store in the previous week, and fixed effects for years and months, for stores, and for holidays, which include Christmas, New Year, Presidents Day, Easter, Memorial Day, 4th of July, Labor Day, Halloween, and Thanksgiving. In panels A and C, the average price in other stores is used as an instrument for the price. In panel B, the log of the wholesale price is used as the instrument for the price. Column 1 gives the unadjusted average of the coefficients. Column 2 gives the quantity-adjusted average of the coefficients. Column 3 gives the revenue-adjusted average of the coefficients. Column 4 (5) gives the number of positive (negative) coefficients. Column 6 (7) gives the number of positive and significant (negative and significant) coefficients. Column 8 gives the total number of observations. In panel A we do not add the quantity in period $t-1$ to the regression. In panel C we use observations from before January 1991. * $p < 10\%$, ** $p < 5\%$, *** $p < 1\%$

Appendix D: Nielsen Data

The Nielsen Retail Scanner Data, which are available from the Kilts Center for Marketing at the Booth School of Business at the University of Chicago, consists of weekly price, sales volume, and store merchandising data reported by participating retail store point-of-sale systems in all US markets. Depending on the year, data are included from approximately 30,000–50,000 participating grocery, drug, mass merchandise, and other retail stores. Products from all Nielsen-tracked categories are included in the data, such as food, non-food grocery items, health and beauty aids, and select general merchandise.

We use the data for 2019. The Nielsen dataset has the advantage that it is large and it is representative of the current US retail market. However, for our purpose, it has two major drawbacks. First, prices in the dataset are quantity-weighted weekly average prices. Therefore, if a price changed during the week, or if some consumers paid a price that is different from the posted price (e.g., when they used a coupon), then the prices reported in the dataset are likely to be different than the prices that consumers paid during the week.

Second, the observations are divided into broad departments, such as "dry grocery," "alcoholic beverages," "dairy," etc. Each department is further divided into product groups. For example, the product groups "bread and baked goods," "fruit – canned" and "juice, drinks – canned, bottled" belong to the dry grocery department. Product groups are further divided into narrowly defined product modules. For example, the "fruit – canned" product group includes 18 modules, including "canned fruit – cherries," and "canned fruit – grapes."

We, therefore, have information on narrowly defined product modules, but we do not have information on where the products were located in the store. Consequently, we do not know whether or not the goods are sold via the front-end display shelves.

To deal with the first problem, we follow Strulov-Shlain (2022) by including in our sample only prices that remain unchanged for at least two weeks in a row. As Strulov-Shlain (2022) shows, this greatly reduces the risk of using prices that were not paid by consumers. This, however, comes at a cost: we lose about 50% of the observations (Strulov-Shlain, 2022).

To deal with the second problem, we looked for modules containing products that are usually placed on the front-end display shelves. We found three such modules: chewing gum, bubble gum, and sugar-free chewing gum.

Because we drop a large number of observations, we do not estimate regressions of price rigidity. Indeed, such regressions would be suspect since we include in our sample only the prices that last at least two weeks in a row. However, we follow Strulov-Shlain (2022) and use the data for estimating demand.

When estimating demand, we have to take into account the fact that we use scanner data. Consequently, we have observations on a good only in weeks in which at least one unit was sold. If we ignore missing observations, therefore, we might overestimate the demand for goods that are bought in small numbers, because we only observe them in weeks in which at least one unit was sold. We, therefore, find for each product (UPC) the number of weeks in which it was sold across all stores and remove the products in the first quartile in terms of the number of weeks for which we have information (Strulov-Shlain, 2022).[6]

Table 1 gives summary statistics of each product module. The average price in these modules is $1.45–$2.28. The average number of units sold per store per week (sales volume) is 4.10–4.31. The number of observations varies between 2,827,275 in the bubble gum product module and 51,571,803 in the sugar-free chewing gum module.

Figure 1 depicts, for each product module, the percentage of observations that ends with each of the possible 10 right-most digits. As may be expected, given that the data comes from large supermarkets, drugstores, etc., the most common price ending is 9. The round endings, 0 and 5, however, are also quite common. In particular, 0-ending prices compose 8.3%–17.8% of all price endings.

[6] We have data for one year, 52 weeks. 26 weeks is therefore half of the maximum possible number of observations.

We estimate demand using a simple demand equation:

$$
\begin{aligned}
&Ln\left(sales\text{-}volume_{i,s,t}\right) \\
&\qquad = \alpha + \beta_1 \times Ln\left(price_{i,s,t}\right) + \beta_2 \times right\text{-}0_{i,s,t} + \beta_3 \times right\text{-}9_{i,s,t} \\
&\qquad + \beta_4 \times competitors`\,price_{i,s,t} + \beta_5 \times Christmas_t + \gamma_{i,s} + \varepsilon_{i,s,t}
\end{aligned}
$$

where sales-volume is the number of units of product i sold in store s in week t. Price is the price of the product. To alleviate the possible problem of endogeneity, we use the average price in other stores in the same week as an instrument for the price. Right-0 is a dummy variable that equals 1 if the price is 0-ending and 0 otherwise. Right-9 is a dummy that equals 1 if the price is 9-ending and 0 otherwise. Competitors' price is the average price of other products in the product's module offered in week *t* in store *s*. Christmas is a dummy variable that equals 1 in the week that includes December 25 and 0 otherwise. γ coefficients are fixed effects for store-product combinations. ε is a random error. We cluster the standard errors by store.

The estimation results are given in Table 2. We find that in all three product modules, the coefficients of 0-ending prices are positive. In the chewing gum and the sugar-free chewing gum product modules, the coefficients are statistically significant at the 1% level. In the bubble gum product module, which is significantly smaller than the other two modules, the coefficient is statistically significant at the 10% level.

The sizes of the coefficients also seem economically significant: 0-ending prices are correlated with an increase of 1.1%–5.3% in sales volumes. 9-ending prices, on the other hand, are correlated with a decrease in sales volumes.

Thus, the results we find corroborate the results we report in the paper. 0-ending prices seem to be positively correlated with sales volumes for products that are usually sold via front-end display shelves. Further, the results we report here are likely to be a lower bound on the effect of 0-ending prices in the front-end candies department, since it is very likely that at least some of the goods in our database were also sold in other departments. The results we report here are therefore likely to be a mixture of the effects of 0-ending prices on the demand for products sold via the front-end display shelves, and those on the demand for products sold elsewhere in the stores.

Table 1. Summary statistics: Chewing gum, bubble gum, and sugar-free chewing gum, AC Nielsen

	Chewing gum	Bubble gum	Sugar-free chewing gum
Average price	1.552 (0.842)	1.451 (0.557)	2.284 (1.122)
Average sales volume	4.101 (5.073)	4.310 (6.056)	4.254 (5.781)
% 0-ending	8.3%	17.8%	10.6%
% 9-ending	56.7%	70.2%	74.1%
Number of UPCs	181	10	733
Number of stores	46,863	30,803	47,136
N	8,142,043	2,827,275	51,571,803

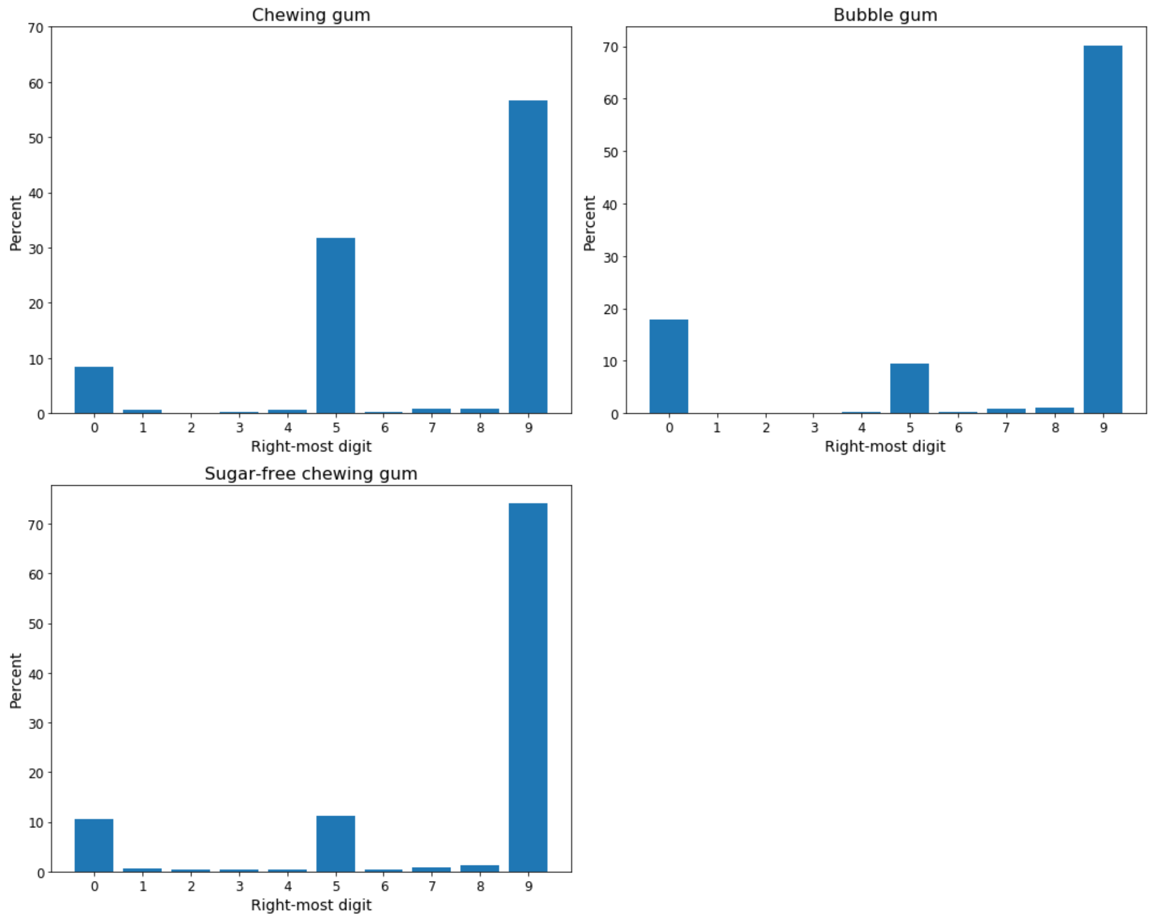
Notes: Summary statistics for products in the chewing gum, bubble gum, and sugar-free chewing gum product modules in the AC Nielsen's database. We remove observations that have prices that last exactly one week. We also remove observations in the lower quartile of the observations over all stores and weeks.

Table 2. Regressions of the effects of price endings on demand in several product modules: AC Nielsen

	Chewing gum	Bubble gum	Sugar-free chewing gum
Right-0	0.029*** (0.003)	0.011* (0.007)	0.053*** (0.002)
Right-9	−0.218*** (0.003)	−0.175*** (0.005)	−0.326*** (0.002)
Ln(price)	−0.997*** (0.016)	0.237*** (0.019)	−0.204*** (0.004)
Ln(competitors-price)	0.009*** (0.001)	−0.006*** (0.002)	−0.009*** (0.002)
Christmas	0.001*** (0.002)	0.114*** (0.003)	0.020*** (0.001)
Constant	1.359*** (0.005)	1.044*** (0.008)	1.361*** (0.004)
R^2	0.057	0.002	0.010
N	8,190,525	2,827,275	51,571,803

Notes: Results of fixed effects regressions of the sales volumes. The dependent variable is the log of the number of units sold of good *i* in store *s* in week *t*. The independent variables are right-0 – a dummy variable that equals 1 if the price is 0-ending and 0 otherwise, right-9 – a dummy variable that equals 1 if the price is 9-ending and 0 otherwise, and ln(price) – the log of the product's price. We use the average price of products in other stores to instrument for the price. Ln(competitors-price) – the average price of other products sold in the same week in the same store. Christmas – a dummy variable that equals 1 in the week that includes December 25 and 0 otherwise. The R^2 is the pseudo overall R^2. Standard errors, clustered at the store level are reported in parentheses. * – $p < 0.10$, **– $p < 0.05$, *** – $p < 0.01$

Figure 1. Percentage of price endings



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