

Asymmetric price adjustment over the business cycle

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Last Revision: June 11, 2025

Abstract: Studies of micro-level price datasets find more frequent *small* price increases than decreases, which can be explained by consumer inattention because time-constrained shoppers might ignore small price changes. Recent empirical studies of the link between shopping behavior and price attention over the business cycle find that consumers are more (less) attentive to prices during economic downturns (booms). These two sets of findings have a testable implication: the asymmetry in small price changes should vary over the business cycle—it should diminish during recessions and strengthen during expansions. We test this prediction using a large US store-level dataset with more than 98 million weekly price observations for the years 1989–1997, which includes an 8-month recession period, as defined by the NBER. We compare price adjustments between periods of recession (high unemployment) and expansion (low unemployment). Focusing on small price changes, we find, consistent with our hypothesis, that there is a greater asymmetry in small price changes during periods of low unemployment compared to the periods of high unemployment, implying that firms' price-setting behavior varies over the business cycle.

JEL Classification:

E31, E32, D11, D21, D80, D91, L11, L16, M31

Keywords:

Asymmetric Price Adjustment

Small Price Changes

Consumer Inattention

Price Rigidity

Sticky Prices

Business Cycles

Unemployment

Recessions

Expansions

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“Because individuals have many things to think about and limited time, they can devote only limited intellectual resources to the tasks of data-gathering and analysis. We know from personal experience that many data that we could look up daily, and that are in principle relevant to our optimal economic decision-making, do not in fact influence our behavior, *except when they change dramatically*, or perhaps when we occasionally set aside some time to re-assess our portfolio” (our emphasis).
Christopher Sims, “Stickiness” (*CRCSP*, 1998, pp. 320–321)

“[Consumers]...face costs of acquiring, absorbing and processing information...[They] rationally choose to only sporadically update their information and re-compute their optimal...plans. In between updating dates, they remain inattentive.”
Ricardo Reis, “Inattentive Consumers” (*JME*, 2006b, p. 1761)

1. Introduction

Many studies of aggregate conditions’ effects on price-setting decisions focus on asymmetric price adjustment.¹ However, studies of the effects of aggregate conditions on the asymmetry in *small* price changes are scarce. To fill this gap in the literature, we study how asymmetry in small price changes varies over the business cycle.

There is evidence of asymmetry in small price changes: there are more frequent small price increases than decreases. The evidence comes from Spain, France, Israel, the USA, Norway, Brazil, the EU, etc., for prices of food, computers, camera equipment, etc.² For example, Chen et al. (2008) study weekly prices of a large US food chain with 98+ million observations for 1989–1997, and find more frequent small price increases than decreases for price changes of up to 10¢–15¢, about 5% of the average price. See Figure 1 (which is similar to Figure 2 in Chen et al., 2008).³

As an explanation, Chen et al. (2008) offer consumer inattention. Time-constrained consumers who buy dozens of goods might be inattentive to small price changes because paying attention to current prices and comparing them to last period’s prices is time-consuming and cognitively demanding (Shugan, 1981). Therefore, the cost of processing information on small price changes might exceed the benefit, creating a range of inattention along the demand curve, where the consumer is inattentive to small price changes.

This range of inattention makes small price *decreases* less valuable to the retailer because slightly lower prices don’t trigger a response from consumers who do not notice the small price cut. A small price *increase*, however, is valuable exactly for the same reason—consumers won’t notice a small price rise and therefore will not reduce purchases. Thus, the retailer has an incentive to make more frequent small price increases than decreases.⁴

It follows that asymmetry should vary with consumer attention: If consumers have more (less) time, and thus are more (less) attentive, we’ll see less (more) asymmetry. Business cycles offer an opportunity to test this prediction, because studies of shopping behavior find a correlation between unemployment and attention: times of high (low) unemployment coincide with greater (less) attention to prices. Thus, high (low) unemployment should coincide with lower (greater) asymmetry in small price changes. That is, as unemployment varies over the cycle, we should see a corresponding variation in consumer attention, and thus, in asymmetry in small price adjustments.

¹ See, for example, Blinder (1991), Hannan and Berger (1991), Mankiw and Romer (1991), Lach and Tsiddon (1992, 1996, 2007), Ball and Mankiw (1994), Blinder et al. (1998), Estrada and Hernando (1999), Peltzman (2000), Mankiw and Reis (2002), Álvarez and Hernando (2004), Davis and Hamilton (2004), and Rotemberg (2005).

² See Buckle and Carlson (2000), Álvarez and Hernando (2004), Baudry et al. (2004), Cecchetti (2004), Rátfai (2004, 2006, 2007), Ellingsen, et al. (2005), Ray et al. (2006, 2012), Lach and Tsiddon (2007), Vermeulen et al. (2007), Chen et al. (2008), Klenow and Kryvtsov (2008), Barros et al. (2009), Reis (2010), Klenow and Malin (2011), Midrigan (2011), Wulfsberg (2016), and Sayag et al. (2024). Eichenbaum et al. (2014), Cavallo and Rigobon (2016), and Cavallo (2018) argue that small price changes could be due to measurement errors. Even these studies, however, find a non-negligible share of small price changes that cannot be explained by measurement errors.

³ Chen et al. (2008) report that their finding is robust. For example, the asymmetry is also present in low-inflation and deflation periods, it holds for alternative measures of inflation and for products whose prices have not increased, and it is robust to lagged price adjustment.

⁴ As Chen et al. (2008, p. 735) note, “The possibility that consumers may be inattentive to price changes is consistent with the observation that retailers alert the public about promotions by posting sale signs, to ensure shoppers *notice* the price discounts” (emphasis in original).

We test this prediction using Chen et al.'s (2008) data, exploiting the fact that their sample period, 1989–1997, contains an 8-month recession. We compare asymmetry in small price changes between the highest and lowest unemployment periods and find that it is indeed stronger when the unemployment rate is low, suggesting that firms' price-setting behavior varies over the business cycle.

Next, we discuss the link between shopping time and price attention. Section 3 discusses testable predictions, Section 4—the data, Section 5—the findings, and Section 6—robustness. Section 7 concludes by summarizing the findings, noting some caveats, and suggesting directions for future research.

2. Shopping time and price attention over the business cycle

The observation that opportunity costs affect price search is well-established. According to Becker (1965, p. 516), "...the unemployed...would be more willing to spend their time in a queue...than would high-earning males." In Stigler's (1961) model, low-income families can cut their expenditures by greater price-attentiveness and search.

Studies of shopping-time variation over the business cycle are consistent with these predictions. Long et al. (2015) find that households pay lower prices when unemployment is high, and that in the Great Recession, when unemployment rose from 5.8% to 9.6%, households adjusted shopping intensity and became more price attentive.

Nevo and Wong (2015) report that in the Great Recession, as unemployment rose, families looked for more deals, made more frequent shopping trips, shopped more at discount stores, used more coupons, and bought more private-label products. Indeed, private label products' share is counter-cyclical.⁵ Cha et al. (2015) report that in the Great Recession, Americans cut restaurant visits and bought more grocery items. In addition, they find that higher unemployment led households to purchase cheaper brands at cheaper outlets.

Aguiar and Hurst (2007) find that older households (whose opportunity cost of time is lower) pay lower prices, shop more intensively, and use more coupons than middle-aged households. Aguiar et al. (2013) find increased shopping-related activities in the Great Recession. McKenzie et al. (2011) find that in the post-2002 crisis, Argentinians increased shopping time and frequency, concluding that "...increase in shopping search is one of the most prevalent adjustment mechanisms used by Argentinian consumers to cope with the crisis" (p. 3).

Lastly, recent studies of informational rigidities also find that people are more attentive in recessions than in expansions (Coibion and Gorodnichenko 2015, Goldstein 2023).

3. Consumer inattention and cyclical variation in price adjustment asymmetry

The consumer inattention argument implies the following hypothesis: during high (low) unemployment, the opportunity cost of time is lower (higher), and thus people are more (less) attentive to small price changes. Also, the value of being attentive to small price changes increases (decreases) in periods of high (low) unemployment. Thus, higher (lower) unemployment would coincide with greater (reduced) attention and therefore, with a lower (higher) asymmetry in small price changes.

We follow Chen et al. (2008, p. 730) to define asymmetry thresholds as "...the last point at which the frequency

⁵ See Volpe (2011, 2014), Dube et al (2018), Marmorstein et al (1992), Hoch and Banerji (1993), Quelch and Harding (1996), Lamey et al (2007).

of price increases exceeds the frequency of price decreases of the same absolute magnitude ($z \geq 1.96$).” In the absence of asymmetry, there should be an equal number of price increases and decreases for each size of price change. Consumer inattention to small price changes implies that we should see more small price increases than small price decreases. The variation in consumer inattention over the business cycle (e.g., unemployment) predicts smaller asymmetry thresholds in periods of high unemployment compared to low unemployment periods.

4. Data

We use the same data as Chen et al. (2008), scanner data from Dominick’s, a large chain in Chicago with 94 stores. The data contains 400 weekly prices over 8 years, Sept. 14, 1989–May 8, 1997, a total of 98,691,750 observations for 18,037 products, in 27 categories.⁶

The 8-year sample period contains an 8-month NBER recession period, from August 1990 to March 1991, which we exploit for comparing the asymmetry during the recession and expansion.

A key macro determinant of consumer attention, as noted above, is unemployment. However, because unemployment lags output by two quarters, the highest and the lowest unemployment periods do not coincide exactly with the recession and expansion periods, respectively.

Therefore, we conduct two analyses. First, we compare the asymmetry thresholds for the *NBER recession months* (capturing the high unemployment effect) with the asymmetry thresholds for the lowest unemployment months. Second, we compare the asymmetry thresholds for the *highest unemployment months* with the asymmetry thresholds for the lowest unemployment months.

We repeat the analysis twice. First, we use the average US unemployment rate to determine the highest and the lowest unemployment rate periods. Second, we use the Chicago unemployment rate to determine the highest and the lowest unemployment rate periods. The latter is useful as Dominick’s operates in the Chicago area. We run the analyses using 8-month windows because the NBER recession in our sample was 8 months long.

As Figure 2 indicates, the period of the lowest US unemployment rate coincides with that of Chicago and occurs in September 1996–April 1997, averaging 4.8% and 5.2%, respectively. The highest unemployment rate period, according to the *u*-US series, is from February 1992–September 1992, averaging 7.6%, while according to the *u*-Chicago series, it is from December 1991–July 1992, averaging 8.1%. During the NBER recession months, the unemployment rate averaged 6.3%.

5. Empirical findings

In the LHS panel of Table 1, we report the asymmetry thresholds.⁷ The cross-category average asymmetry threshold for the lowest unemployment period, $\bar{A} = 10.30\%$, is larger than for the NBER recession period $\bar{A} =$

⁶ For more details about the data, see Dutta et al. (2002), Barsky et al. (2003), Chen et al. (2008), Levy et al. (2002, 2010, 2011, 2020), Snir et al. (2022), and Dominick’s Data User Manual, available at https://www.chicagobooth.edu/-/media/enterprise/centers/kilts/datasets/dominicks-dataset/dominicks-manual-and-codebook_kiltscenter, accessed March 23, 2025. The data is publicly available and it can be downloaded from the homepage of the University of Chicago’s Booth School of Business, www.chicagobooth.edu/research/kilts/datasets/dominicks, accessed March 23, 2025.

⁷ There is only one “Lowest-*u*” column because, as noted above, the periods in which the US and Chicago unemployment rates attain the lowest average values over an 8-month period coincide.

0.62¢, for the Highest- u Chicago period $\bar{A} = 4.15\text{¢}$, and for the Highest- u US period, $\bar{A} = 3.59\text{¢}$.

Across the 27 categories, in 62 out of 75 comparisons (82.7% of cases), we find a stronger asymmetry for the lowest unemployment period, in 5 cases (6.7% of cases) we find equal asymmetry, and in 8 cases (10.7% of cases), we find weaker asymmetry for the lowest unemployment period than for the other periods (Chakraborty et al. 2015). The theoretical prediction of inattention is statistically supported: 82.7% > 50% with $z = 5.65$, $p < 0.0001$. A paired t -test confirms this conclusion: for the 27 product categories, the asymmetry is larger for the lowest unemployment period ($\bar{A} = 10.30$, $SD = 7.99$) than for the other three periods ($\bar{A}_{\text{NBER}} = 0.62$, $SD = 1.02$, $t_{20} = 5.18$, $p < 0.001$; $\bar{A}_{\text{Chicago}} = 4.15$, $SD = 4.75$, $t_{26} = 3.43$, $p < 0.005$; $\bar{A}_{\text{US}} = 3.59$, $SD = 4.09$, $t_{26} = 3.91$, $p < 0.001$).

We find 2.5–16.6 times stronger asymmetry when unemployment is low. Thus, the data is consistent with the consumer inattention hypothesis, irrespective of the criterion used for identifying the high-unemployment period.

6. Robustness

The finding is unlikely to be driven by sample size differences. Although the lowest unemployment period has a larger sample size than the other three periods, the statistical significance of the differences is not high. A paired t -test of the sample size averages yields the following results: lowest- u vs NBER recession, $t_{20} = 2.52$, $p < 0.02$; lowest- u vs highest- u Chicago, $t_{26} = 1.54$, $p > 0.10$; and lowest- u vs highest- u US, $t_{26} = 1.13$, $p > 0.10$.

Also, if we focus on the product categories where the sample size is smaller for the lowest unemployment period, then among the 25 such cases, the difference in asymmetry threshold is in the right direction in 21 cases; it is the same in 1 case (in the cereals category, the lowest- u period vs. the highest- u US), and it is in the opposite direction in 3 cases (in the cereals category: the lowest- u period vs. the highest- u Chicago, and in the toothbrush category: the lowest- u period vs. the highest- u Chicago, and the lowest- u period vs. the highest- u US). The average asymmetry threshold is significantly bigger in the lowest- u period ($\bar{A} = 11.52$, $SD = 7.37$) than in the highest- u periods ($\bar{A} = 3.24$, $SD = 4.32$; $t_{24} = 3.93$, $p < 0.001$).⁸

We repeated the same comparison for each of the three highest-unemployment sample periods separately. Among the 5 cases where the sample size is smaller for the lowest unemployment period than the NBER recession period, the average asymmetry is larger in the lowest- u period ($\bar{A} = 16$, $SD = 5.92$ vs $\bar{A} = 0.40$, $SD = 0.55$, $t_4 = 5.96$, $p = 0.002$). Among the 10 cases where the sample size is smaller for the lowest- u period than the highest- u Chicago, the average asymmetry is bigger in the lowest- u period, but the difference is not statistically significant ($\bar{A} = 10.40$, $SD = 10.4$ vs $\bar{A} = 5.10$, $SD = 5.95$, $t_9 = 1.34$, $p = 0.21$). Among the 10 cases where the sample size is smaller for the lowest- u period than the highest- u US, the average asymmetry is significantly bigger in the lowest- u period ($\bar{A} = 10.40$, $SD = 8.07$ vs $\bar{A} = 2.80$, $SD = 2.78$, $t_9 = 2.64$, $p < 0.03$). We conclude that the differences in asymmetry thresholds are unlikely to be driven by differences in sample sizes.

Could our findings be an artifact of the negative SR inflation-unemployment relationship? In that case, the

⁸ $\bar{A} = 11.52$ is the average of the asymmetry thresholds for the 25 low-unemployment cases. $\bar{A} = 3.24$ is the average of the three asymmetry thresholds for the high unemployment periods: NBER recession, Highest- u Chicago, and Highest- u US.

finding of smaller asymmetry thresholds during the highest unemployment would imply that there was deflation during that specific period. We therefore look at the inflation rates for the three 8-month periods, using the PPI, CPI-US, and CPI-Chicago (Table A1 in the Appendix). If we compare the 8 months with the highest unemployment to the 8 months with the lowest unemployment, the average inflation rate is higher for the former (for all three indices). The results are the same if we compare the 8 months with the lowest unemployment with the NBER recession period. The unemployment rate is higher in the recession, but the inflation rate is also higher (for all three indices). We conclude that our findings are unrelated to the inflation-unemployment relationship.

Another explanation might be that in high-unemployment periods, there are more price cuts if retailers try to boost sales in economic downturns. However, price cuts should not affect asymmetry thresholds systematically because in Dominick's data, they are temporary and therefore reversed (Rotemberg 2005, Chen et al 2008, Midrigan 2011). For robustness, we explored this by identifying sales events using a V-shaped sales filter of Syed (2015) and Fox and Syed (2016) and excluding them from the analysis.⁹

The figures in Table A2 in the appendix indicate that the main results are unaffected. The asymmetry threshold for the lowest unemployment period, $\bar{A} = 10.85\%$, is larger than for the NBER recession period $\bar{A} = 0.48\%$, for the Highest- u Chicago period $\bar{A} = 3.78\%$, and for the Highest- u US period $\bar{A} = 2.81\%$. Across the 27 categories, in 56 out of 75 comparisons, i.e., in 74.67% of cases, we find a stronger asymmetry for the lowest unemployment period, in 5 cases (6.7% of the cases) equal asymmetry, and in 14 cases (18.67% of the cases) weaker asymmetry for the lowest unemployment period than for the other periods.

We also considered the effects of clearance sales on our results by identifying instances where products are withdrawn following a price cut of 10% or more and excluding them from the analysis. As the figures in Table A3 in the appendix show, the asymmetry thresholds we obtain here are no different from what we report in Table 1.

We rerun the analysis by simultaneously excluding both the V-shaped sales events and clearance sales. The results reported in Table A4 in the appendix are similar to what we report in Table A2 in the appendix.

We conclude that excluding V-shaped sales and clearance sales does not alter our key results: In most cases, the asymmetry in small price changes is stronger in booms than in busts, as hypothesized.

7. Conclusion, caveats, and future work

Chen et al. (2008) explain asymmetric price adjustment in small price changes by consumer inattention to small price changes, giving the sellers the incentive to make more frequent small price increases than decreases. Recent studies find a correlation between shoppers' attention to prices and unemployment: the higher the unemployment, the more attentive shoppers are to prices. These two sets of findings lead to a testable prediction: we should see a variation in the extent of asymmetry in small price adjustments over the business cycle. During booms (busts), because the unemployment rate is low (high) and shoppers are less (more) attentive, we should see greater (lesser) asymmetry in small price adjustments.

⁹ The literature offers about a dozen different sales filters (Sandler et al. 2024). The filter of Syed (2015) and Fox and Syed (2016) is calibrated for Dominick's price data, making it particularly useful for us. The filter is used by Snir and Levy (2021) and Snir et al. (2022). Note that we used a sales filter rather than Dominick's sale indicator dummy because the latter was not set consistently (Peltzman 2000).

We use large scanner data for 1989–1997, which includes an 8-month recession, to compare the asymmetry in small price changes between the recession (high u) and expansion (low u) periods. Consistent with our hypothesis, we find a greater asymmetry in small price changes during low-unemployment periods, compared with high-unemployment periods, implying that firm price-setting behavior varies over the business cycle.

We shall note, however, that we study a single (although quite large) chain over a period that contains a single cycle of low and high unemployment. It will be useful, therefore, if future work further explores these questions using different datasets over other periods of recessions and expansions, to provide additional evidence of how asymmetry in small price adjustments varies over the business cycle.

Acknowledgments

We are grateful to the anonymous reviewer for constructive comments and suggestions that improved the manuscript and to the editor, Eric Young, for guidance. We thank various conference and seminar participants for their helpful discussions. The views expressed herein are those of the authors and not necessarily those of the Federal Reserve Bank of Minneapolis or the Federal Reserve System. All errors are ours.

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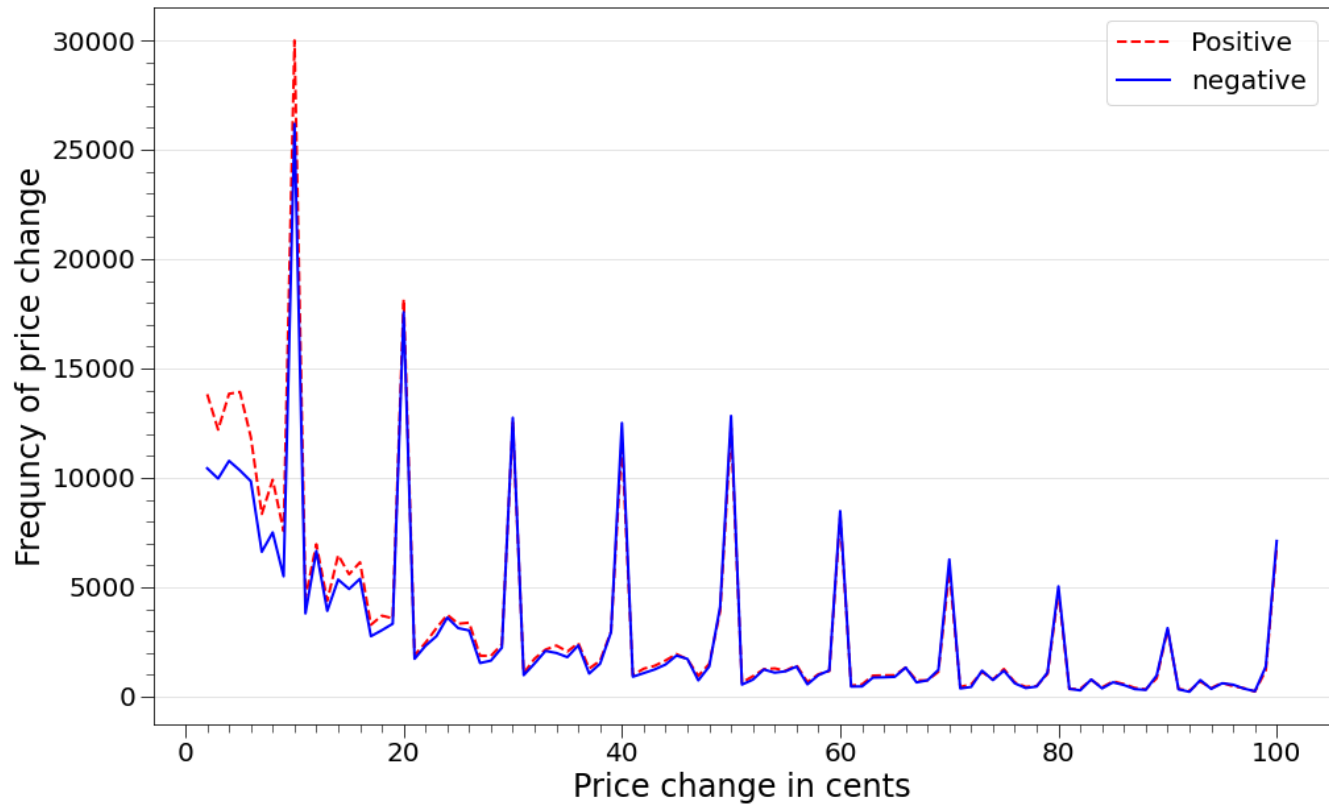


Fig. 1. Average frequency of positive and negative price changes, all 29 categories

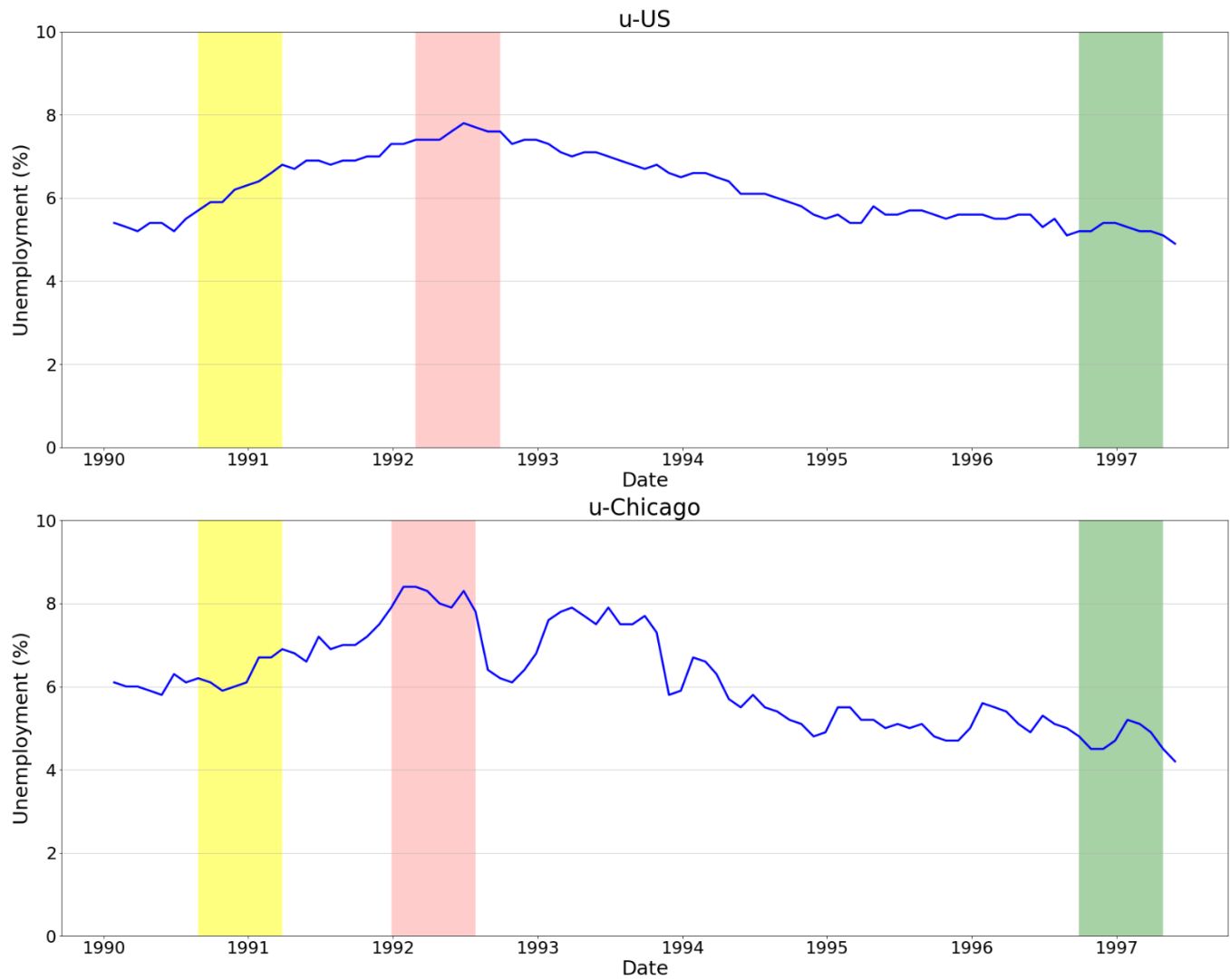


Fig. 2. Monthly unemployment rate in the US and Chicago, 1989–1997

Notes:

1. The left-hand side shaded area marks the NBER recession period, August 1990–March 1991.
2. The middle-shaded area marks the highest unemployment rate periods, February 1992–September 1992 in the US, and December 1991–July 1992 in Chicago.
3. The right-hand side shaded area marks the lowest unemployment periods, September 1996–April 1997, in both the US and Chicago.

Table 1

Variation in the asymmetry threshold in cents over the business cycle

Product Categories	Asymmetry threshold (\bar{A}) in cents				Sample size			
	Lowest u	NBER Recession	Highest- u Chicago	Highest- u US	Lowest u	NBER Recession	Highest- u Chicago	Highest- u US
Analgesics	16	0	8	8	290,098	243,554	275,751	271,589
Bath Soap	0	--	0	4	66,850	--	29,693	40,445
Bathroom Tissues	4	3	1	1	119,928	81,772	95,866	97,704
Bottled Juices	12	2	6	6	396,630	296,436	398,069	400,885
Canned Soup	17	0	1	1	270,074	480,363	510,137	513,003
Canned Tuna	25	1	2	2	169,238	204,450	225,749	229,596
Cereals	0	0	20	0	444,826	435,170	465,991	469,343
Cheeses	29	0	1	1	640,023	545,066	590,552	594,712
Cookies	9	1	8	6	629,269	658,658	720,327	724,924
Crackers	11	0	1	1	267,978	184,937	198,575	194,353
Dish Detergent	15	0	2	2	208,650	192,674	191,233	191,155
Fabric Softeners	1	0	4	3	195,268	180,544	190,898	193,299
Front-end-candies	16	0	1	1	339,746	391,849	409,466	414,510
Frozen Dinners	9	--	7	3	219,267	--	52,357	104,752
Frozen Entrees	19	0	11	8	666,595	595,097	626,024	627,971
Frozen Juices	10	0	2	1	200,042	190,792	209,811	211,856
Grooming Products	18	--	10	10	686,463	--	292,428	408,529
Laundry Detergents	13	0	2	2	239,687	256,294	301,483	304,595
Oatmeal	4	--	0	18	116,311	--	112,143	107,397
Paper Towels	2	0	1	1	81,136	73,354	84,240	83,448
Refrigerated Juices	15	0	10	1	207,171	149,588	177,756	176,872
Shampoos	17	--	3	6	816,157	--	493,778	683,457
Snack Crackers	3	1	2	2	309,361	297,408	301,817	304,149
Soaps	9	--	1	1	226,417	--	183,734	214,697
Soft Drinks	3	3	0	0	1,262,488	658,506	774,846	791,416
Toothbrushes	0	0	8	8	168,467	162,515	187,868	192,626
Toothpastes	1	2	0	0	294,654	238,442	251,899	252,323
Average Threshold (\bar{A})	10.30	0.62	4.15	3.59				
Median	10	0	2	2				

Notes:

1. Lowest u denotes the lowest unemployment rate period for both the City of Chicago and the US.
2. NBER Recession denotes the NBER recession period.
3. Highest- u Chicago denotes the highest Chicago unemployment rate period.
4. Highest- u US denotes the highest U.S. unemployment rate period.
5. The empty cells are the cases of missing observations.

Online Supplementary Web Appendix

(Not for Publication)

Asymmetric Price Adjustment over the Business Cycle

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Table A1

Three measures of inflation (*PPI*, *CPI*, and *CPI-Chicago*) and two measures of unemployment (*u*-US and *u*-Chicago), September 1989–May 1997

Year	Month	<i>PPI</i>	% Δ <i>PPI</i>	<i>CPI</i>	% Δ <i>CPI</i>	<i>CPI-Chicago</i>	% Δ <i>CPI-Chicago</i>	<i>u</i> -US	<i>u</i> -Chicago
1989	September	113.6	-	125.0	-	127.1	-	5.3	-
1989	October	114.9	1.14	125.6	0.5	126.8	-0.2	5.3	-
1989	November	114.9	0.00	125.9	0.2	126.7	-0.1	5.4	-
1989	December	115.4	0.44	126.1	0.2	126.5	-0.2	5.4	-
1990	January	117.6	1.91	127.4	1.0	128.1	1.3	5.4	6.1
1990	February	117.4	-0.17	128.0	0.5	129.2	0.9	5.3	6.0
1990	March	117.2	-0.17	128.7	0.5	129.5	0.2	5.2	6.0
1990	April	117.2	0.00	128.9	0.2	130.4	0.7	5.4	5.9
1990	May	117.7	0.43	129.2	0.2	130.4	0.0	5.4	5.8
1990	June	117.8	0.08	129.9	0.5	131.7	1.0	5.2	6.3
1990	July	118.2	0.34	130.4	0.4	132.0	0.2	5.5	6.1
1990	August	119.3	0.93	131.6	0.9	133.2	0.9	5.7	6.2
1990	September	120.4	0.92	132.7	0.8	133.8	0.5	5.9	6.1
1990	October	122.3	1.58	133.5	0.6	133.3	-0.4	5.9	5.9
1990	November	122.9	0.49	133.8	0.2	134.2	0.7	6.2	6.0
1990	December	122.0	-0.73	133.8	0.0	134.6	0.3	6.3	6.1
1991	January	122.3	0.25	134.6	0.6	135.1	0.4	6.4	6.7
1991	February	121.4	-0.74	134.8	0.1	135.5	0.3	6.6	6.7
1991	March	120.9	-0.41	135.0	0.1	136.2	0.5	6.8	6.9
1991	April	121.1	0.17	135.2	0.1	136.1	-0.1	6.7	6.8
1991	May	121.8	0.58	135.6	0.3	136.8	0.5	6.9	6.6
1991	June	121.9	0.08	136.0	0.3	137.3	0.4	6.9	7.2
1991	July	121.6	-0.25	136.2	0.1	137.3	0.0	6.8	6.9
1991	August	121.7	0.08	136.6	0.3	137.6	0.2	6.9	7.0
1991	September	121.4	-0.25	137.2	0.4	138.3	0.5	6.9	7.0
1991	October	122.2	0.66	137.4	0.1	138.0	-0.2	7.0	7.2
1991	November	122.3	0.08	137.8	0.3	138.0	0.0	7.0	7.5
1991	December	121.9	-0.33	137.9	0.1	138.3	0.2	7.3	7.9
1992	January	121.8	-0.08	138.1	0.1	138.9	0.4	7.3	8.4
1992	February	122.1	0.25	138.6	0.4	139.2	0.2	7.4	8.4
1992	March	122.2	0.08	139.3	0.5	139.7	0.4	7.4	8.3
1992	April	122.4	0.16	139.5	0.1	139.8	0.1	7.4	8.0
1992	May	123.2	0.65	139.7	0.1	140.5	0.5	7.6	7.9
1992	June	123.9	0.57	140.2	0.4	141.2	0.5	7.8	8.3
1992	July	123.7	-0.16	140.5	0.2	141.4	0.1	7.7	7.8
1992	August	123.6	-0.08	140.9	0.3	141.9	0.4	7.6	6.4
1992	September	123.3	-0.24	141.3	0.3	142.7	0.6	7.6	6.2
1992	October	124.4	0.89	141.8	0.4	142.1	-0.4	7.3	6.1
1992	November	124.0	-0.32	142.0	0.1	142.4	0.2	7.4	6.4
1992	December	123.8	-0.16	141.9	-0.1	142.9	0.4	7.4	6.8
1993	January	124.2	0.32	142.6	0.5	143.2	0.2	7.3	7.6
1993	February	124.5	0.24	143.1	0.4	143.6	0.3	7.1	7.8
1993	March	124.7	0.16	143.6	0.3	144.1	0.3	7.0	7.9
1993	April	125.5	0.64	144.0	0.3	144.7	0.4	7.1	7.7
1993	May	125.8	0.24	144.2	0.1	145.7	0.7	7.1	7.5
1993	June	125.5	-0.24	144.4	0.1	145.6	-0.1	7.0	7.9
1993	July	125.3	-0.16	144.4	0.0	145.5	-0.1	6.9	7.5
1993	August	124.2	-0.88	144.8	0.3	146.1	0.4	6.8	7.5

1993	September	123.8	-0.32	145.1	0.2	146.7	0.4	6.7	7.7
1993	October	124.6	0.65	145.7	0.4	147.2	0.3	6.8	7.3
1993	November	124.5	-0.08	145.8	0.1	146.4	-0.5	6.6	5.8
1993	December	124.1	-0.32	145.8	0.0	146.1	-0.2	6.5	5.9
1994	January	124.5	0.32	146.2	0.3	146.5	0.3	6.6	6.7
1994	February	124.8	0.24	146.7	0.3	146.8	0.2	6.6	6.6
1994	March	124.9	0.08	147.2	0.3	147.6	0.5	6.5	6.3
1994	April	125.0	0.08	147.4	0.1	147.9	0.2	6.4	5.7
1994	May	125.3	0.24	147.5	0.1	147.6	-0.2	6.1	5.5
1994	June	125.6	0.24	148.0	0.3	148.1	0.3	6.1	5.8
1994	July	126.0	0.32	148.4	0.3	148.3	0.1	6.1	5.5
1994	August	126.5	0.40	149.0	0.4	149.8	1.0	6.0	5.4
1994	September	125.6	-0.71	149.4	0.3	150.2	0.3	5.9	5.2
1994	October	125.8	0.16	149.5	0.1	149.4	-0.5	5.8	5.1
1994	November	126.1	0.24	149.7	0.1	150.4	0.7	5.6	4.8
1994	December	126.2	0.08	149.7	0.0	150.5	0.1	5.5	4.9
1995	January	126.6	0.32	150.3	0.4	151.8	0.9	5.6	5.5
1995	February	126.9	0.24	150.9	0.4	152.3	0.3	5.4	5.5
1995	March	127.1	0.16	151.4	0.3	152.6	0.2	5.4	5.2
1995	April	127.6	0.39	151.9	0.3	153.1	0.3	5.8	5.2
1995	May	128.1	0.39	152.2	0.2	153.0	-0.1	5.6	5.0
1995	June	128.2	0.08	152.5	0.2	153.5	0.3	5.6	5.1
1995	July	128.2	0.00	152.5	0.0	153.6	0.1	5.7	5.0
1995	August	128.1	-0.08	152.9	0.3	153.8	0.1	5.7	5.1
1995	September	127.9	-0.16	153.2	0.2	154.0	0.1	5.6	4.8
1995	October	128.7	0.63	153.7	0.3	154.3	0.2	5.5	4.7
1995	November	128.7	0.00	153.6	-0.1	154.0	-0.2	5.6	4.7
1995	December	129.1	0.31	153.5	-0.1	153.8	-0.1	5.6	5.0
1996	January	129.4	0.23	154.4	0.6	154.6	0.5	5.6	5.6
1996	February	129.4	0.00	154.9	0.3	155.2	0.4	5.5	5.5
1996	March	130.1	0.54	155.7	0.5	156.3	0.7	5.5	5.4
1996	April	130.6	0.38	156.3	0.4	156.4	0.1	5.6	5.1
1996	May	131.1	0.38	156.6	0.2	156.9	0.3	5.6	4.9
1996	June	131.7	0.46	156.7	0.1	157.6	0.4	5.3	5.3
1996	July	131.5	-0.15	157.0	0.2	157.7	0.1	5.5	5.1
1996	August	131.9	0.30	157.3	0.2	158.1	0.3	5.1	5.0
1996	September	131.8	-0.08	157.8	0.3	158.3	0.1	5.2	4.8
1996	October	132.7	0.68	158.3	0.3	158.8	0.3	5.2	4.5
1996	November	132.6	-0.08	158.6	0.2	159.4	0.4	5.4	4.5
1996	December	132.7	0.08	158.6	0.0	159.7	0.2	5.4	4.7
1997	January	132.6	-0.08	159.1	0.3	160.4	0.4	5.3	5.2
1997	February	132.2	-0.30	159.6	0.3	161.1	0.4	5.2	5.1
1997	March	132.1	-0.08	160.0	0.3	161.0	-0.1	5.2	4.9
1997	April	131.6	-0.38	160.2	0.1	160.9	-0.1	5.1	4.5
1997	May	131.6	0.00	160.1	-0.1	161.1	0.1	4.9	4.2

Notes

Yellow: August 1990–March 1991 - NBER Recession Months - 8 months

Navy: September 1996–April 1997 - Chicago - Lowest unemployment rate 8-month period, $\bar{u} = 4.8\%$

Green: September 1996–April 1997 - US - Lowest unemployment rate 8-month period, $\bar{u} = 5.2\%$

Blue: February 1992–September 1992 - US - Highest unemployment rate 8-month period, $\bar{u} = 7.6\%$

Purple: December 1991–July 1992 - Chicago - Highest unemployment rate 8-month period, $\bar{u} = 8.1\%$

Table A2

Variation in the asymmetry thresholds in cents over the business cycle, after excluding V-shaped sales events

Product Categories	Asymmetry threshold (\bar{A})				Sample size			
	Lowest u	NBER Recession	Highest- u Chicago	Highest- u US	Lowest u	NBER Recession	Highest- u Chicago	Highest- u US
Analgesics	0	0	8	8	247,027	194,952	256,879	254,113
Bath Soap	0	--	0	4	62,201	--	25,841	34,529
Bathroom Tissues	3	0	0	0	100,972	60,383	60,969	63,685
Bottled Juices	32	2	0	0	335,060	230,481	293,839	291,778
Canned Soup	16	0	0	0	220,292	410,157	443,668	447,123
Canned Tuna	10	1	0	0	149,901	159,343	176,287	184,184
Cereals	0	0	21	0	399,987	397,768	427,337	398,884
Cheeses	32	0	0	0	510,315	398,904	428,277	433,358
Cookies	20	0	0	0	480,465	527,293	547,184	536,090
Crackers	23	0	0	0	198,120	123,084	141,456	140,516
Dish Detergent	12	0	0	0	180,224	153,348	158,044	157,446
Fabric Softeners	1	0	0	0	170,769	144,974	157,918	154,171
Front-end-candies	5	0	1	0	312,058	368,840	364,181	375,411
Frozen Dinners	1	--	18	5	156,394	--	35,949	68,925
Frozen Entrees	10	0	11	9	479,724	457,468	453,459	448,185
Frozen Juices	14	0	1	0	155,118	141,441	157,220	158,265
Grooming Products	18	--	0	10	535,251	--	234,010	330,053
Laundry Detergents	10	0	1	1	203,769	214,815	240,892	239,516
Oatmeal	4	--	0	14	98,187	--	102,935	101,272
Paper Towels	1	0	0	0	68,403	50,007	58,732	58,362
Refrigerated Juices	10	0	11	0	155,013	88,334	104,080	102,328
Shampoos	10	--	3	8	622,122	--	396,415	543,336
Snack Crackers	2	1	1	1	228,789	214,795	201,254	221,418
Soaps	11	--	0	0	197,827	--	146,843	173,222
Soft Drinks	48	3	13	3	740,748	382,807	428,307	444,675
Toothbrushes	0	0	8	8	115,268	132,646	167,911	166,280
Toothpastes	0	3	5	5	225,329	193,596	217,500	211,898
Average Threshold (\bar{A})	10.85	0.48	3.78	2.81				
Median	10	0	0	0				

Notes:

1. Lowest u denotes the lowest unemployment rate period, for both the City of Chicago and the U.S.
2. NBER Recession denotes the NBER recession period.
3. Highest- u Chicago denotes the highest Chicago unemployment rate period.
4. Highest- u US denotes the highest U.S. unemployment rate period.
5. The blank cells are the cases of missing observations

Table A3

Variation in the asymmetry thresholds in cents over the business cycle, after excluding clearance sales events

Product Categories	Asymmetry threshold (\bar{A})				Sample size			
	Lowest u	NBER Recession	Highest- u Chicago	Highest- u US	Lowest u	NBER Recession	Highest- u Chicago	Highest- u US
Analgesics	16	0	8	8	290,042	243,467	275,733	271,554
Bath Soap	0	--	0	4	66,836	--	29,681	40,433
Bathroom Tissues	4	3	1	1	119,903	81,770	95,849	97,684
Bottled Juices	12	2	6	6	396,211	296,320	398,011	400,841
Canned Soup	17	0	1	1	269,942	480,339	510,137	513,003
Canned Tuna	25	1	2	2	169,220	204,371	225,702	229,552
Cereals	0	0	20	0	444,768	435,156	465,938	469,266
Cheeses	29	0	1	1	639,059	545,034	590,486	594,571
Cookies	9	1	8	6	629,066	658,632	720,165	724,731
Crackers	11	0	1	1	267,800	184,936	198,548	194,290
Dish Detergent	15	0	2	2	208,618	192,469	191,221	191,147
Fabric Softeners	1	0	4	3	195,080	180,434	190,736	193,136
Front-end-candies	16	0	1	1	339,727	391,759	409,453	414,472
Frozen Dinners	9	--	7	3	219,161	--	52,326	104,702
Frozen Entrees	19	0	11	8	665,977	594,446	625,524	627,418
Frozen Juices	10	0	2	1	200,032	190,737	209,737	211,780
Grooming Products	18	--	10	10	685,873	--	292,341	408,311
Laundry Detergents	13	0	2	2	239,502	255,708	301,281	304,449
Oatmeal	4	--	0	18	116,309	--	112,142	107,396
Paper Towels	2	0	1	1	81,125	73,332	84,184	83,394
Refrigerated Juices	15	0	10	1	207,081	149,455	177,736	176,825
Shampoos	17	--	3	6	815,200	--	493,357	682,806
Snack Crackers	3	1	2	2	309,279	297,382	301,704	304,060
Soaps	9	--	1	1	226,341	--	183,608	214,570
Soft Drinks	3	3	0	0	1,260,976	658,340	774,370	790,879
Toothbrushes	0	0	8	8	168,319	162,481	187,857	192,607
Toothpastes	1	2	0	0	294,477	238,394	251,796	252,000
Average Threshold (\bar{A})	10.30	0.62	4.15	3.59				
Median	10	0	2	2				

Notes:

1. Lowest u denotes the lowest unemployment rate period, for both the City of Chicago and the U.S.
2. NBER Recession denotes the NBER recession period.
3. Highest- u Chicago denotes the highest Chicago unemployment rate period.
4. Highest- u US denotes the highest U.S. unemployment rate period.
5. The blank cells are the cases of missing observations

Table A4

Variation in the asymmetry thresholds in cents over the business cycle, after simultaneously excluding V-shaped sales and clearance sales events

Product Categories	Asymmetry threshold (\bar{A})				Sample size			
	Lowest u	NBER Recession	Highest- u Chicago	Highest- u US	Lowest u	NBER Recession	Highest- u Chicago	Highest- u US
Analgesics	0	0	8	8	247,027	194,952	256,877	254,111
Bath Soap	0	--	0	4	62,201	--	25,841	34,529
Bathroom Tissues	3	0	0	0	100,972	60,383	60,969	63,685
Bottled Juices	32	2	0	0	335,060	230,481	293,839	291,778
Canned Soup	16	0	0	0	220,292	410,154	443,668	447,123
Canned Tuna	10	1	0	0	149,901	159,336	176,285	184,184
Cereals	0	0	21	0	399,987	397,768	427,337	398,882
Cheeses	32	0	0	0	510,315	398,904	428,271	433,352
Cookies	20	0	0	0	480,465	527,289	547,179	536,086
Crackers	23	0	0	0	198,120	123,084	141,455	140,508
Dish Detergent	12	0	0	0	180,224	153,348	158,043	157,446
Fabric Softeners	1	0	0	0	170,769	144,972	157,905	154,158
Front-end-candies	5	0	1	0	312,058	368,832	364,181	375,411
Frozen Dinners	1	--	18	5	156,394	--	35,946	68,921
Frozen Entrees	10	0	11	9	479,724	457,455	453,442	448,152
Frozen Juices	14	0	1	0	155,118	141,441	157,220	158,265
Grooming Products	18	--	0	10	535,251	--	234,005	330,044
Laundry Detergents	10	0	1	1	203,769	214,787	240,890	239,514
Oatmeal	4	--	0	14	98,187	--	102,935	101,272
Paper Towels	1	0	0	0	68,403	50,003	58,727	58,359
Refrigerated Juices	10	0	11	0	155,013	88,334	104,080	102,328
Shampoos	10	--	3	8	622,122	--	396,398	543,317
Snack Crackers	2	1	1	1	228,789	214,795	201,247	221,411
Soaps	11	--	0	0	197,827	--	146,835	173,214
Soft Drinks	48	3	13	3	740,748	382,802	428,281	444,646
Toothbrushes	0	0	8	8	115,268	132,645	167,909	166,278
Toothpastes	0	3	5	5	225,329	193,596	217,499	211,897
Average Threshold (\bar{A})	10.85	0.48	3.78	2.81				
Median	10	0	0	0				

Notes:

1. Lowest u denotes the lowest unemployment rate period, for both the City of Chicago and the U.S.
2. NBER Recession denotes the NBER recession period.
3. Highest- u Chicago denotes the highest Chicago unemployment rate period.
4. Highest- u US denotes the highest U.S. unemployment rate period.
5. The blank cells are the cases of missing observations