TECHNICAL APPENDIX

Asymmetric Wholesale Pricing: Theory and Evidence

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TECHNICAL APPENDIX – Data

This appendix addresses the concern regarding our wholesale data: *Could the Results be an Artifact of How the Wholesale Prices Are Calculated?*

Our wholesale price, as reported in the Dominick's database, is based on the average acquisition cost (AAC). The AAC per unit is calculated as follows:

$$AAC(t) = \frac{\{Purch(t) \times price(t)\} + \{EndInventory(t-1) - sales(t)\} \times AAC(t-1)}{TotalInventory(t)}$$

where,

Purch(t) = Inventory bought in t;

price(t) = Per unit wholesale price paid in t;

EndInventory(t-1) = Inventory at end of t-1;

Sales(t) = Retail sales at t;

TotalInventory(t) = Total Inventory at t

Lagged adjustment of AAC

Can it be claimed that our results could be just an artifact of the manner in which AAC is calculated? Manufacturers often inform the retailer in advance of an impending temporary price reduction, permitting the retailer to completely deplete its inventory and then "*forward-buying*" to overstock at the lower price (Peltzman, 2000). Since new purchases form a large proportion of the total inventory in this case, the large discount shows up as a commensurately large reduction in AAC. On the other hand, a retailer buys *less* when the wholesale price goes up. Consequently, a wholesale price *increase* of the same large magnitude as the decrease considered earlier, will translate into a relatively smaller increase in AAC (the so called, lagged adjustment). It is reasonable to expect that the observed asymmetry in wholesale prices therefore may be driven by such forward buying phenomenon.

In the absence of actual wholesale prices, how do we conduct a direct test to check for the above effect? One way of proceeding is to check the data for patterns implied by the above rationale. We discuss the following analyses in the same spirit.

National Brands versus Private Labels

Note that the forward buying rationale suggests that *if the manner of calculating AAC was the major driver of our results (asymmetry in the small), it should be more pronounced for products that are subjected to greater degree of forward buying*. For products not subject to major fluctuations in its purchases driven by promotional prices, we should expect much lesser degree of such systematic distortion. This leads to the following null proposition which holds true if the manner of computing AAC was the major driver of our results.[1]

> Forward Buying Proposition: Products subject to greater degree of forward buying will exhibit greater asymmetry than products that are subject to lesser degree of forward buying.

Unfortunately, we do not have direct data on the degree of forward buying. However, according to Hoch et al. (1995), private labels are not promoted as heavily, and hence are forward-bought less than national brands. Therefore, a comparison of national brands to private labels provides a natural context to test the above proposition. In essence, if forward buying is the main driver of our results, the predicted asymmetry should be stronger for national brands than for private labels. We therefore undertook two additional analyses to explore whether, and to what extent, can our results be attributed to the method of computing AAC. In the paragraphs below we first discuss the data and then the individual tests.

National Brand versus Private Label Data

For the purposes of the test we need data on comparable national brand (NB)-private label (PL) product pairs. We base our identification of such NB-PL pairs on a recently published study of Barsky, et al (2003), who use the same Dominick's data to investigate the size of markups for nationally branded products sold in the U.S. retail grocery industry. Their measure of markup is based on a comparison of the prices of matched pairs of NB-PL products. To implement their strategy, therefore, Barsky, et al. (2003) had to identify the product pairs based on several comparability criteria, which included, among other attributes, product's quality, size, packaging, etc. For quality comparison, they used Hoch and Banerji's (1993) PL product quality rankings.

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[1] This is not to be confused with our theoretical proposition earlier. Here we intend to check if the "null," (forward buying is a key driver of the observed asymmetry), can be rejected in favor of the "alternate" (that it is not).

After filtering out the product pairs that were not comparable for various reasons (for example, size differences, quality differences, insufficient number of observations, etc.), Barsky, et al. (2003) were left with 231 matched NB-PL product pairs of comparable size and quality, covering 19 product categories.[2] These categories are Analgesics, Bottled Juices, Cereals, Cheeses, Cookies, Crackers, Canned Soups, Dish Detergent, Frozen Entrees, Frozen Juices, Fabric Softeners, Grooming Products, Laundry Detergent, Oatmeal, Snack Crackers, Tooth Pastes, Toothbrushes, Soft Drinks, and Canned Tuna. However, Barsky, et al. (2003) argue that Toothbrushes category is an outlier for its unusually high markup ratio, in comparison to the remaining 18 categories. Consequently, they omit the Toothbrushes category from much of their analysis.[3] Following their strategy, therefore, we also exclude the category of Toothbrushes from our analysis and were left with 18 categories with matched NB-PL pairs for our analyses.

Analysis 1: Comparison of aggregate asymmetries between NB and PL

We start by conducting an analysis identical to that used in the main paper and compare the aggregate asymmetry *thresholds* between NB and PL pairs for all the 18 categories. The hypothesis below is derived directly from the null proposition.[4]

Hypothesis 1: Aggregate asymmetry threshold for National Brands is greater than that for Private Labels.

Tables R2.1 and R2.2 below report the results of the analysis in terms of absolute changes (Cents) and relative changes (%), respectively. The thresholds we obtain are marked in bold. In the absolute case we obtain an asymmetry threshold of 6 cents for the national brands (NB) and 5 cents for private labels (PL). In the relative case, we obtain *identical* thresholds of 4%.

Two important observations are in order here. First, note the *similarity* of the magnitudes of the thresholds in both the tests. So, while we cannot subject Hypothesis 1 to a statistical test of significance and are limited to comparing two numbers, the prima facie evidence argues against the hypothesis.

[2] See Barsky, et al. (2003), Tables 7A.1-7A.19 for a detailed list of the NB-PL product pairs.
[3] See Barsky, et al., 2003, p. 194.
[4] This and all subsequent hypotheses derived from the null proposition are in the nature of null hypotheses which we aim to reject in favor of the alternate proposition that forward buying is not a key driver.

Second, note the presence of *significant asymmetry for the PL sample*. This last point is important because if forward buying indeed were a primary driver of our observed asymmetry and if PLs are not subjected to significant forward buying, we should expect only insignificant asymmetry for the PL sample. But that is not the case and the asymmetry for PLs is not only significant but comparable to that of NBs.

Table R2.1: Frequencies of price changes for the 18 categories with NB-PL pairs (Cents)

Price Change in Cents	NB Positive	NB Negative	NB Z-Value	PL Positive	PL Negative	PL Z-Value
1	4496	3550	10.546	4788	3348	15.965
2	2117	1683	7.040	2473	1833	9.753
3	1398	1097	6.026	1482	1369	2.116
4	1048	860	4.304	1121	912	4.635
5	823	727	2.438	**895**	**736**	**3.937**
6	**661**	**517**	**4.196**	682	644	1.044
7	542	493	1.523	551	472	2.470
8	489	429	1.980	361	397	1.308
9	415	330	3.114	365	332	1.250
10	382	306	2.897	324	272	2.130
11	270	295	1.052	364	255	4.381

Table R2.2: Frequencies of price changes for the 18 categories with NB-PL pairs (%)

Price Change in %	NB Positive	NB Negative	NB Z-Value	PL Positive	PL Negative	PL Z-Value
1	4072	3304	8.942	4480	3220	14.359
2	1893	1512	6.529	2156	1613	8.845
3	1300	1056	5.027	1431	1138	5.781
4	**905**	**795**	**2.668**	**1061**	**887**	**3.942**
5	648	592	1.590	758	746	0.309
6	566	526	1.210	634	612	0.623
7	428	432	0.136	497	536	1.213
8	416	394	0.773	415	467	1.751
9	311	369	2.224	392	415	0.810
10	321	292	1.171	459	362	3.385
11	257	226	1.411	340	336	0.154

Taken together, these observations provide strong evidence that our results are not entirely driven by the manner of computing AAC. In the subsequent analyses, we conduct further tests to explore the robustness of this statement.

Let the degree of asymmetry in a given price change be the difference between the number of positive and negative changes expressed as a percentage of the number of positive changes. For example, the degree of asymmetry for 1 Cent difference is calculated as: (#POS 1 Cent changes - #NEG 1Cent changes)/#POS 1 Cent changes. Like earlier, if forward buying is indeed the primary driver of the asymmetry in AAC, we should expect that it would reflect in a greater mean degree of asymmetry for NB compared to PL. This leads to the following hypothesis.

Hypothesis 2: Aggregate degree of asymmetry for National Brands is greater than that for Private Labels.

The difference between hypothesis 1 and hypothesis 2 is that while the first considered asymmetry thresholds, the second considers the extent of asymmetry between positive and negative changes.

To conduct this test, we first calculated the degree of asymmetry for each price change and then compared the mean asymmetry between NB and PL with a paired t-test. We conducted the test for both absolute (Cents) and relative (%) changes. Given the thresholds of 6 cents for NB and 5 cents for PL in absolute terms, and 4% for both in relative terms, we restricted the comparison to small magnitudes (1-11 Cents and 1-11%) in order to focus on the region of interest.[5] Table R2.3a below reports the mean degrees of asymmetry we observe and the results of the paired t-tests. In the absolute case, we observe an average degree of asymmetry of 15.2% for NB and 15.0% for PL. For the relative case, the averages are 8.4% and 8.3% for NB and PL respectively. Notice that none of the comparisons are significant (p = 0.485 and 0.493 respectively), i.e. we find *no* support for hypothesis 2.

In order to make sure that we did not ignore any possible regions where such asymmetry might exist, we repeated the analysis successively for 1-5 Cents, 1-6 Cents, 1-7 Cents, 1-8 Cents, 1-9 Cents and 1-10 Cents as well as for 1-5%, 1-6%, 1-7%, 1-8%, 1-9% and 1-10% bands. In none of these 12 additional comparisons was there any significant difference in the average degree of asymmetry between NB and PL (all p's > 0.30).

[5] This also has the added advantage of being a strong test because any difference between NB and PL due to forward buying is more likely to manifest in the small. We also checked even smaller ranges.

Table R2.3a: Comparison of average degree of asymmetry between NB and PL

	Absolute (Cents)		Relative (%)	
	NB	PL	NB	PL
Mean Degree of Asymmetry	15.2%	15.0%	8.4%	8.3%
t-stat	0.039		0.019	
p value	0.485		0.493	

In addition to the tests above, we checked the degree of asymmetry of the PL sample. As argued earlier, if forward buying indeed were a primary driver of our observed asymmetry and if PLs are not subjected to significant forward buying, we should not expect any significant asymmetry for the PL sample. To test this we checked if the mean degrees of asymmetry of the PL sample were significantly greater than zero. The results are in Table R2.3b below. For both (absolute and elative) cases, the means are significantly greater than zero ($p<0.05$).

Table R2.3b: Mean degree of asymmetry of PL sample

	(Absolute - Cents)	(Relative - %)
Mean	0.149965	0.083003
t-stat	4.213	1.913
Sig.	p<0.05	p<0.05

(H0: μ=0)

Therefore, in keeping with the conclusions following Hypothesis 1, the results of the above analyses provide strong evidence that our results cannot be entirely driven by the manner of computing AAC. We now drill down further into the data and look at even more disaggregate comparisons.[6]

Analysis 2: Comparison of category level asymmetries between NB and PL

For this investigation, we conducted an analysis identical to that used in the main paper, and compared the asymmetry thresholds between NB and PL for individual categories. The hypothesis below is derived directly from the proposition.

Hypothesis 3: The average category level asymmetry threshold for National Brands is greater than that for Private Labels.

[6] Note however, that our sample size becomes very small as we drill down to more disaggregate levels.

To test this hypothesis, we first obtained the asymmetry thresholds for both NB and PL in individual categories and then compared the average threshold with a paired t-test. The analysis is conducted for both absolute (Cents) as well as relative (%) changes. Table R2.4a below reports the mean asymmetry thresholds we observe and the results of the paired t-tests. In the absolute case, we observe an average degree of asymmetry of 1.111 for NB and 1.389 for PL. For the relative case, the averages are 0.944% and 1.556% for NB and PL respectively. Notice that none of the comparisons are significant (p = 0.280 and 0.091 respectively), i.e. we find *no* support for hypothesis 3.

Table R2.4a: Comparison of average category level asymmetry thresholds between NB and PL

	Absolute (Cents)		Relative (%)	
	NB	PL	NB	PL
Mean Threshold of Asymmetry	1.111	1.389	0.944%	1.556%
t-stat	-0.589		-1.364	
p value	0.280		0.091	

In addition, we also checked the average category level asymmetry thresholds for the PL sample. In keeping with the arguments made earlier, we should not expect significant asymmetry in this sample if forward buying was the primary driver of our observed asymmetry. We test if the average category level asymmetry thresholds for the PL sample are significantly greater than zero. The results are in table R2.4b. In both (absolute and relative) cases, the average thresholds are significantly greater than zero ($p<0.05$)

Table R2.4b: Average category level asymmetry threshold for PL sample

	(Absolute - Cents)	(Relative - %)
Mean	1.389	1.556
T	4.034	4.932
Sig.	p<0.05	p<0.05

(H0: m=0)

Again, in keeping with the conclusions following Hypotheses 1 and 2, the results of the above analyses provide *additional* evidence that our results cannot be entirely driven by the manner of computing AAC.

Nevertheless, in search of further robustness, we continue the investigation in greater detail by comparing *individual* category level thresholds in the following analysis. In conducting this analysis however, we feel compelled to point out the drastic loss of sample size that occurs. For example, the average number of observations per category in the data set, is 3,431,118, while the average number of observations for each NB-PL pair for a category is only 3,710, a reduction in excess of 99%. Therefore, the comparisons should be kept in perspective – they are likely to be more illustrative in nature and perhaps more accurate in a relative sense than in an absolute sense.

Table R2.5 below reports the asymmetry thresholds we obtain for each NB-PL pair. The analysis is repeated for both absolute (cents) and relative (%) changes. We also report the sample size for each pair in the last column.

The results reported in this table provide additional support to our claims following Hypotheses 1, 2 and 3, that our results cannot be entirely driven by the manner of computing AAC. This is based on the following three observations.

Observation 1: Out of the 18 product categories for which we have data, 3 didn't show asymmetry for either absolute or relative changes; 12 showed the asymmetry for either absolute or relative changes and showed an asymmetry threshold for private labels that is as large as or larger than national brands; 3 showed the asymmetry for either absolute or relative change and showed a larger asymmetry threshold for national brands than for private labels. Therefore, the proportion of product categories for which the prediction of forward buying is supported is less than chance level (i.e., 3/15 < 50%; $z = 2.32$; $p < 0.03$).

Observation 2: Out of 36 (= 18 x 2) possible comparisons, there are five that are consistent with the prediction of forward buying (marked in bold in the table). However, 15 are in the opposite direction and in the remaining 16 cases the threshold is the same for private labels and national brands.[7] Altogether, the majority of comparisons (i.e., 31, or more than 86%) are *inconsistent* with the prediction of forward buying.

[7] 8 of which have an asymmetry threshold of 0 for both NB and PL – an observation that we feel is driven by the severely limited sample size.

Observation 3: For comparisons where there is a non-zero threshold for either NB or PL, there are 15 for which the threshold is larger for PL than for NB, compared to 5 for which the opposite is true. The difference is statistically significant ($z = 2.27$, $p < .03$).

Table R2.5: Asymmetry thresholds for the 18 categories with NB-PL pairs

Categories	Absolute (Cents)		Relative (%)		
	NB	PL	NB	PL	Sample Size
Analgesics	1	1	3	3	5149
Bottled Juices	3	3	1	2	6735
Canned Soup	3	3	**4**	**2**	6136
Canned Tuna	0	0	0	0	919
Cereals	3	3	3	4	6111
Cheeses	1	1	0	1	3021
Cookies	2	2	0	1	3513
Crackers	**1**	**0**	**1**	**0**	2410
Dish Detergent	0	2	0	1	2756
Fabric Softeners	0	0	0	0	2060
Frozen Entrees	0	5	0	3	636
Frozen Juices	2	2	1	3	6587
Grooming Products	0	0	0	0	667
Laundry Detergents	0	2	0	1	3930
Oatmeal	0	0	1	3	920
Snack Crackers	0	0	0	1	1017
Soft Drinks	0	1	0	3	10623
Tooth Pastes	**4**	**0**	**3**	**0**	3593
Total (all 18 categories combined)	**6**	**5**	4	4	66783

Bold: NB > PL

To conclude, we do not find any strong reason to believe that the forward buying hypothesis related to AAC is a primary driver of our results. We subject the data to a series of tests to check if there are patterns consistent with the forward buying hypotheses. None of the analyses, whether descriptive or statistical, provide support for these hypotheses. In the absence of such evidence, we conclude that it is highly unlikely that our empirical results are an artifact of the manner in which the wholesale prices have been calculated.

Such a conclusion must however, be tempered with the knowledge that we are after all dealing with a derived measure of wholesale prices and a better test of our theory would be with actual wholesale prices. Unfortunately, such data is not available. We are not unique in dealing with this problem. A number of other authors who have dealt with it bemoan the lack of proper wholesale price data (*cf*. Cecchetti, 1986; Peltzman, 2000; Chintagunta, 2002; Levy, et al. 2002;

Chevalier, et al. 2003 etc.). Creative approaches like estimating wholesale prices from regression which is particularly common in the empirical industrial organization literature (see Carlton and Perloff, 1994), using aggregate price indexes, such as wholesale price index, as a proxy (Cecchetti, 1985), rough accounting estimates (Nevo, 2001), even simulation (Tellis and Zufryden, 1995) are the norm in such cases. Others may ignore explicit consideration of wholesale prices altogether (Gerstner et al., 1994; Pesendorfer, 2001).

While the lack of accurate wholesale price data is unfortunate, we believe that should not hinder theory building in the domain of wholesale prices. Nevertheless, the onus is on the researcher to ensure that any empirical test of theory using weak wholesale data is actually robust to the weakness of the data. It is in that spirit that we conducted these additional checks.

To keep things in perspective therefore, it is necessary to understand that while we stand behind the spirit of our results, we recognize that the verity of the exact magnitudes of the asymmetry we report is subject to some uncertainty.

Reverse Asymmetry in the large

It may be worthwhile here, to consider the role of reverse asymmetry in the large vis-à-vis the forward buying proposition. When a manufacturer offers a temporary off-invoice discount to a retailer, the retailer tends to buy more of the product than it needs during the period of the sale. AAC typically falls by a large amount then. Theoretically, if this drop in AAC is not matched by a similar increase when prices do go up, one should see reverse asymmetry in the large. Since retailers are normally expected to purchase lesser amounts at higher prices, this leads us to believe that *reverse asymmetry in the large* – i.e. more large price decreases than increases, is a reasonable prediction if the rival forward buying hypothesis was a primary driver of our results.

The method we employed to test this is to compare, for each of the 29 product categories, the frequencies in which positive price changes exceeded negative price changes (“positive” asymmetry), with the frequencies in which the opposite holds true (“negative” asymmetry). If the alternative, lagged adjustment is the main driver, then we should observe relatively more frequent occurrences of negative than positive asymmetry in the large. If there is no such negative asymmetry in the large, as our theory predicts, then occurrences of the number of positive and negative asymmetries should be statistically equal. We report the number of occurrences of positive (p) and negative asymmetries (n) as a ratio (p:n) in Table R2.6[8] We carried out the analyses for the entire sample, as well as for a sample of low/zero inflation period and a sample of deflation period. We also did the analyses both in terms of absolute changes in cents and in terms of percentage changes.

Table R2.6: Number of Positive vs. Negative Asymmetry Beyond Threshold

	Entire Sample Period		Low/Zero Inflation Period		Deflation Period	
	Absolute (Cents)	Relative (%)	Absolute (Cents)	Relative (%)	Absolute (Cents)	Relative (%)
Analgesics	16:1	17:20	21:3	13:18	28:8	14:18
Bath Soap	11:11	26:15	13:15	24:18	12:13	21:14
Bathroom Tissues	10:15	26:12	11:18	32:10	13:15	33:10
Beer	**2:43****	29:14	**3:34****	29:13	15:21	27:12
Bottled Juices	15:11	26:16	9:10	24:12	20:16	25:14
Canned Soup	19:11	21:13	17:13	17:13	21:16	19:16
Canned Tuna	22:10	24:13	14:17	19:19	16:14	17:15
Cereals	10:1	**5:27**	22:2	17:19	16:8	16:21
Cheeses	14:11	25:14	13:16	22:21	20:11	21:17
Cigarettes	23:8	20:15	22:22	14:20	**9:33****	18:19
Cookies	15:19	23:17	16:16	21:19	15:19	17:19
Crackers	12:13	22:18	17:15	20:19	18:15	19:18
Dish Detergent	16:16	23:16	**8:24****	23:17	**9:28****	26:16
Fabric Softeners	13:21	23:19	13:20	22:13	**10:19****	21:15
Front-end-candies	21:15	**11:25****	14:24	**8:31****	18:18	**6:34****
Frozen Dinners	21:17	22:20	29:11	22:21	24:13	19:22
Frozen Entrees	7:8	18:24	10:15	**13:26****	19:17	17:24
Frozen Juices	**8:21****	23:15	13:21	24:11	17:17	19:8
Grooming Products	18:11	26:13	12:12	26:14	19:12	26:11
Laundry Detergents	13:12	21:23	**8:21****	19:23	14:11	17:20
Oatmeal	36:2	17:20	41:3	21:21	26:8	19:21
Paper Towels	19:12	26:8	16:15	22:16	9:16	23:12
Refrigerated Juices	20:7	26:16	18:15	25:17	19:14	22:17
Shampoos	11:13	27:16	24:11	23:18	20:13	22:18
Snack Crackers	25:11	29:12	15:21	22:20	17:20	25:19
Soaps	7:10	29:10	19:4	32:7	22:4	33:8
Soft Drinks	19:7	**13:25****	20:11	14:24	15:17	16:24
Tooth Brushes	17:15	23:15	13:16	21:18	16:17	20:20
Tooth Pastes	12:11	23:17	12:21	26:15	13:20	27:12
Total (All 29 Categories Combined)	7:4	20:20	12:12	17:23	15:11	19:22

**** There are more frequent occurrences of negative asymmetry than positive asymmetry ($p < .05$).

The results in Table R2.6 do not support the alternative explanation that lagged adjustment is driving our result. Specifically, with any of the six tests we did, there were three or fewer

[8] For example, the ratio 13:12 for Laundry Detergents suggests that there were 13 occurrences of positive to 12 occurrences of negative asymmetries.

product categories in which there were more negative than positive asymmetry in the large, in a statistically significant sense ($z>1.65$, $p<0.05$). Similarly, when all the 29 product categories were combined, there was statistically equal number of positive and negative asymmetry in the large.

However, we acknowledge that it is not clear whether this by itself is a strong test. Reverse asymmetry in the large appears to be highly contextual and dependent on several factors. After procuring a large amount of the product at a low cost, the retailer normally quits buying for several periods while going through its inventory. How AAC adjusts subsequently, is a function of a number of things including the remaining inventory, quantity purchased, and wholesale prices when the retailer starts buying again. The hypothesized reverse asymmetry will hold if the retailer starts buying small quantities before the forward bought inventory is largely depleted. However, if the retailer waits till the entire inventory is depleted before restocking its entire inventory at a higher price, then we may not see the reverse asymmetry in the large.[9]

In our analysis it is difficult to control for these different inventory practices. Nevertheless, for situations where the reverse asymmetry is not predicted, i.e. where the retailer restocks at a higher price only after depleting its forward bought inventory, it is not clear that asymmetry in the small will be driven by forward buying. It is possible that for such products forward buying is no longer a rival explanation for our finding of asymmetric pricing in the small. For the other inventory practices (re-ordering in small quantities before depletion of the forward bought inventory) on the other hand, it appears theoretically reasonable to predict reverse asymmetry in the large simultaneously with asymmetry in the small.

We understand either can be true, and maybe it's a combination of both practices. Nevertheless, even if it is a combination of both practices, reverse asymmetry in the large may be a reasonable check. Either the inventory pattern occurs often enough to be a rival explanation for our asymmetric pricing patterns (in which case one should expect reverse asymmetry to be prevalent) or it does not happen often enough to generate reverse asymmetry (in which case asymmetric pricing should not be prevalent, so the rival explanation of forward buying is not a

[9] We assume that the entire inventory is replenished in this case and that the prices go back up at the point of repurchase. For certain cases, prices may not go back up to previous levels. For such smaller increases, the prediction of reverse asymmetry holds along with that of asymmetry in the small.

problem for our theory). So, we believe, albeit not perfect, the lack of reverse asymmetric pricing in the large is not a wholly unreasonable metric of the validity of our results.

We do not find any evidence of such reverse asymmetry in our data. In combination with the results comparing national brands and private labels, we would like to believe this is further corroborating evidence that our empirical results (asymmetry in the small) are not driven by forward buying.

Changes in Manufacturer's Pricing Policies from September 1994

The last check on the measure of wholesale price data concerns a change in the manufacturers' pricing policies during the sample period. Starting September 1994, manufacturers in the Dominick's dataset adopted retrospective discounts, whereby they offered rebates based on sales in a specified period rather than offering a direct discount. It is not clear how this change might affect the AAC. Earlier studies using the same dataset therefore often restrict their sample up to September 1994 (e.g. Peltzman, 2000; page 472). To rule out that our results may be driven by this change, we conduct an additional analysis by restricting the sample to the period September 1989 to August 1994. We find that our central result – that of asymmetry in the small and symmetry in the large consistently holds in this restricted sample.

Table R2.7 reports the absolute (cents) and relative (%) thresholds obtained for the pre-September 1004 sample, while Table R2.8 reports the number of instances of positive and negative asymmetries observed beyond the thresholds for the same sample. There are statistically equal numbers of positive and negative asymmetries when the entire sample is considered ($p>0.05$). In a category level analysis, in 40 out of 58 (i.e., 69%) instances, there are statistically equal numbers of positive and negative asymmetries. More positive than negative asymmetry is observed only in 8 instances out of 58 possible comparisons (13.8%). It happened for 3 product categories in terms of absolute changes, and 5 product categories in terms of relative changes. More negative than positive asymmetry happened in only 10 instances out of 58 possible comparisons (17.2%). It happened for 6 product categories in terms of absolute changes, and 4 product categories in terms of relative changes. Overall therefore, our central results (asymmetry in the small but symmetry in the large remains unchanged for the pre-September 1994 sample, thereby ruling out the pricing policy change as a driver of our results.

Table R2.7. What Might Constitute a "Small" Price Change?
Statistical Analysis of the Data by Product Category in Absolute (¢) and Relative (%) Terms
Subsample: Sept. 1989 - - August 1994

Categories	Absolute (Cents)	Relative (%)
Analgesics	26	25
Bath Soap	5	5
Bathroom Tissues	5	2
Beer	12	6
Bottled Juices	14	9
Canned Soup	14	13
Canned Tuna	3	3
Cereals	23	10
Cheeses	12	14
Cigarettes	1	1
Cookies	4	9
Crackers	3	2
Dish Detergent	7	3
Fabric Softeners	8	4
Front-end-candies	6	7
Frozen Dinners	7	3
Frozen Entrees	1	1
Frozen Juices	0	0
Grooming Products	14	9
Laundry Detergents	14	4
Oatmeal	10	7
Paper Towels	1	1
Refrigerated Juices	10	3
Shampoos	10	3
Snack Crackers	3	2
Soaps	9	11
Soft Drinks	2	3
Tooth Brushes	15	1
Tooth Pastes	10	6
Total (all 29 product categories combined)	20	10

Below the thresholds of number of positive changes are significantly more than number of negative changes ($p<0.05$).

Table R2.7. Number of Positive vs. Negative Asymmetry Beyond Threshold
Subsample: Sept. 1989 - - August 1994

	Absolute (Cents)		Relative (%)	
	Positive asymmetry	Negative asymmetry	Positive asymmetry	Negative asymmetry
Analgesics	16	13	9	11
Bath Soap	12	16	20	13
Bathroom Tissues	16	19	12*	27*
Beer	17	15	19	19
Bottled Juices	8*	21*	15	14
Canned Soup	17	9	27**	6**
Canned Tuna	17	20	19	12
Cereals	13**	3**	15	17
Cheeses	17	9	17**	5**
Cigarettes	0*	12*	1*	13*
Cookies	21	14	27**	13**
Crackers	16	20	26	15
Dish Detergent	12	17	17	19
Fabric Softeners	9*	22*	14	22
Front-end-candies	5*	21*	27**	3**
Frozen Dinners	15	22	15	16
Frozen Entrees	27	19	18	24
Frozen Juices	16	19	26	16
Grooming Products	7*	20*	8*	24*
Laundry Detergents	12	15	17	19
Oatmeal	15	8	11	13
Paper Towels	17	16	21	15
Refrigerated Juices	9*	24*	19	12
Shampoos	13	13	24	14
Snack Crackers	18	11	25	15
Soaps	22**	10**	20**	8**
Soft Drinks	27**	13**	14*	31*
Tooth Brushes	16	12	22	13
Tooth Pastes	14	17	20	16
Total (all 29 product categories combined)	14	11	23	14

**: More positive than negative asymmetry.
*: More negative than positive asymmetry. .
(p < .05).

TECHNICAL APPENDIX – Future Extension of Model

Speculative comments regarding extending the model to n-periods

In the paper, we have shown why asymmetric adjustment of wholesale prices is a subgame perfect equilibrium in a 2-period model. It is interesting to posit what the nature of the equilibrium will be when we extend the game to longer time horizons. Such extension can be done in several ways.

One way of extending the game would be to consider additional time periods. For simplicity, we can begin with assuming no additional change in upstream costs beyond those existing in the current model. If for example, the manufacturer was to set price for *n-1* future periods instead of just one. Since now the retailer would face a cost x in *each* future period, it may allow the manufacturer to incorporate the *cumulative* degree of retailer's rigidity in the price it sets following the initial period. Knowing this, the retailer would of course set a commensurately different initial price. The magnitude of the wholesale asymmetry $|\Delta w^*|$ derived for the 2-period solution will then be modified by at least two factors – (a) the number of time periods being considered, n, and (b) the magnitude of discount factor, δ. Taking the liberty to speculate, it stands to reason that the magnitude of the modification will likely be some transformation $G(|\Delta w^*|; n,\delta)$, where $\sum G/\sum n > 0$ and $\sum G/\sum \delta < 0$. Substantively therefore, this is unlikely to be different from the results and conclusions we draw from our simpler model. It could be further complicated with additional changes in costs (and related uncertainty), which will likely lead to similar results, although it is not clear how these complexities would be likely to change the central results of the two period model.

We can also consider another model emphasizing *repeated* price setting games, with the manufacturer actions being asymmetric or symmetric pricing in *each* period. Manufacturer payoffs in any given period in such a game could be contingent on its historical pricing behavior. This could be achieved in several ways, e.g. by explicitly giving the retailer the choice of imposing penalties or even by invoking some sort of reputation mechanisms. The equilibrium outcome is less certain here. For an infinitely repeated 2-player game, the Folk Theorem would predict that "any combination of actions observed in any finite number of repetitions is the unique outcome of some subgame perfect equilibrium" as long as the rate of time preference (the discount factor) is sufficiently small and the probability that the game ends in any repetition is sufficiently small (Rasmusen, 2002; page 112). This would suggest that asymmetric pricing cannot be completely ruled out, yet may be only one of many possible outcomes, even when manufacturers expect to be in a continued relationship with the retailer. Nevertheless, these extensions are beyond the scope of our model and we can merely speculate as to the likely outcomes of such a setup.

In this context, an observation relevant for our purposes is that there is significant uncertainty in the duration of relationships between manufacturers and retailers. While manufacturers and retailers often engage over long time horizons, supermarkets frequently drop not only individual SKUs but sometimes also entire categories from their product portfolio. As Peltzman (2000, p. 500) notes, "Occasionally (the) leading items in a category is either introduced or replaced (within a given observation period)." Turnover in brands is also not uncommon. Manufacturers may also change the pricing format (see Peltzman's paper, page 500). These suggest that it may be more accurate to model the pricing game as being of a *finite* duration. In that case, it is reasonable to speculate that our results will hold and asymmetry will be an equilibrium outcome.[10] Again, these conjectures are beyond the scope of the model we currently have in the paper. However, these are certainly interesting and worthy of future research in the area.

Conjectures aside, in the final analysis, a benefit of making the retailers forward looking in the model is that – in equilibrium retailers are not disadvantaged by asymmetric pricing in the small – they adjust their initial pricing decisions to reflect this economic reality. That was another reason why this was such a valuable extension of the model.[11] So it is not clear that a richer space of punishments, relationships or prices would necessarily be of any improvement to the retailer in this situation. The costs of price adjustment are real, and as such any solution would have to factor them into the equilibrium.

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[10] See the discussion in Rasmusen (2002) of the Chainstore Paradox originally explained by Selten (1978).
[11] We thank the reviewers and editors for guiding us to explore this direction – it greatly improved the paper.

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TECHNICAL APPENDIX – FIGURES

Category Level Plots of Asymmetric Wholesale Pricing

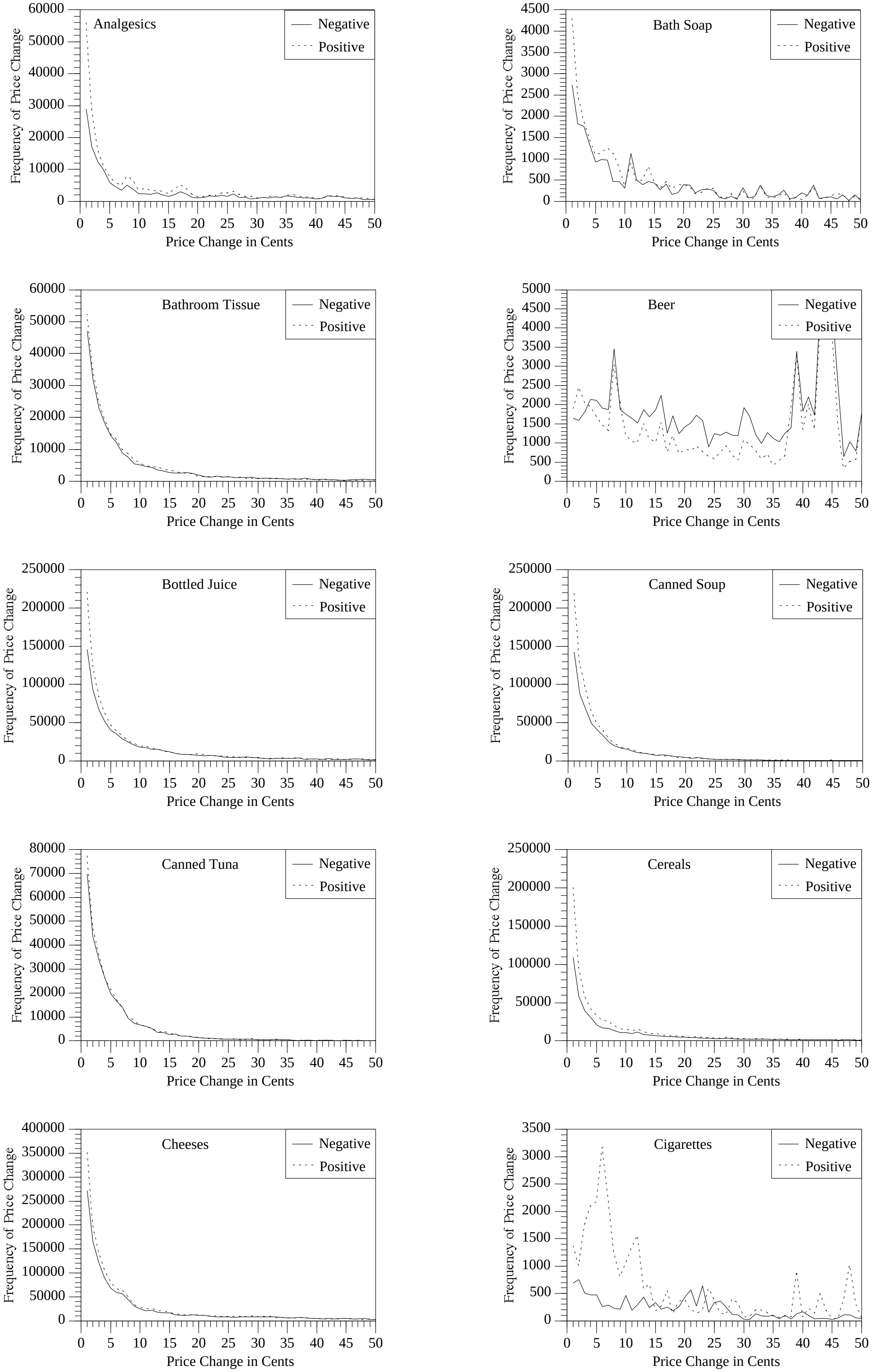


Figure 1.1a. Frequency of Positive and Negative Wholesale Price Changes in Cents by Category

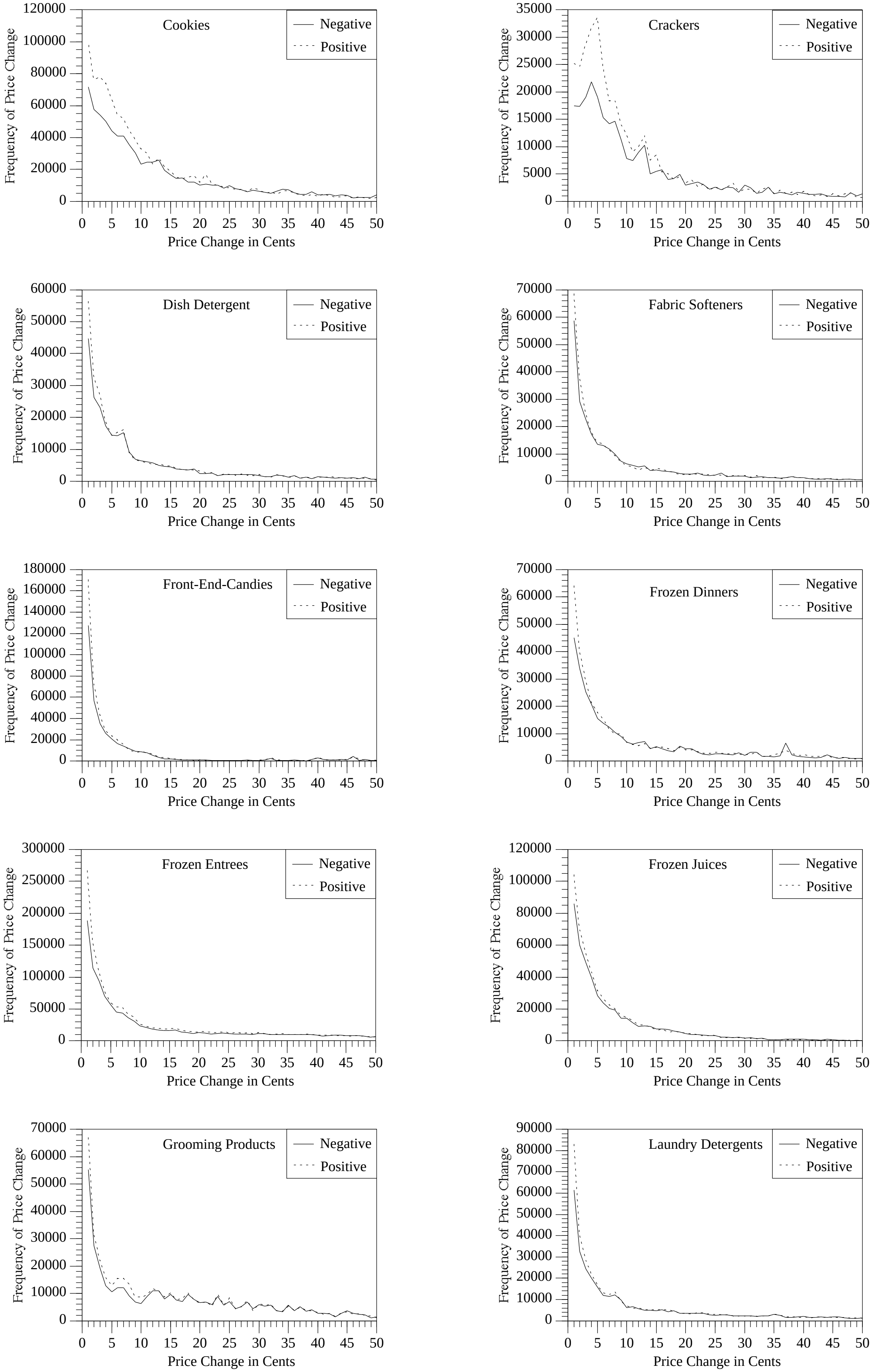


Figure 1.1b. Frequency of Positive and Negative Wholesale Price Changes in Cents by Category

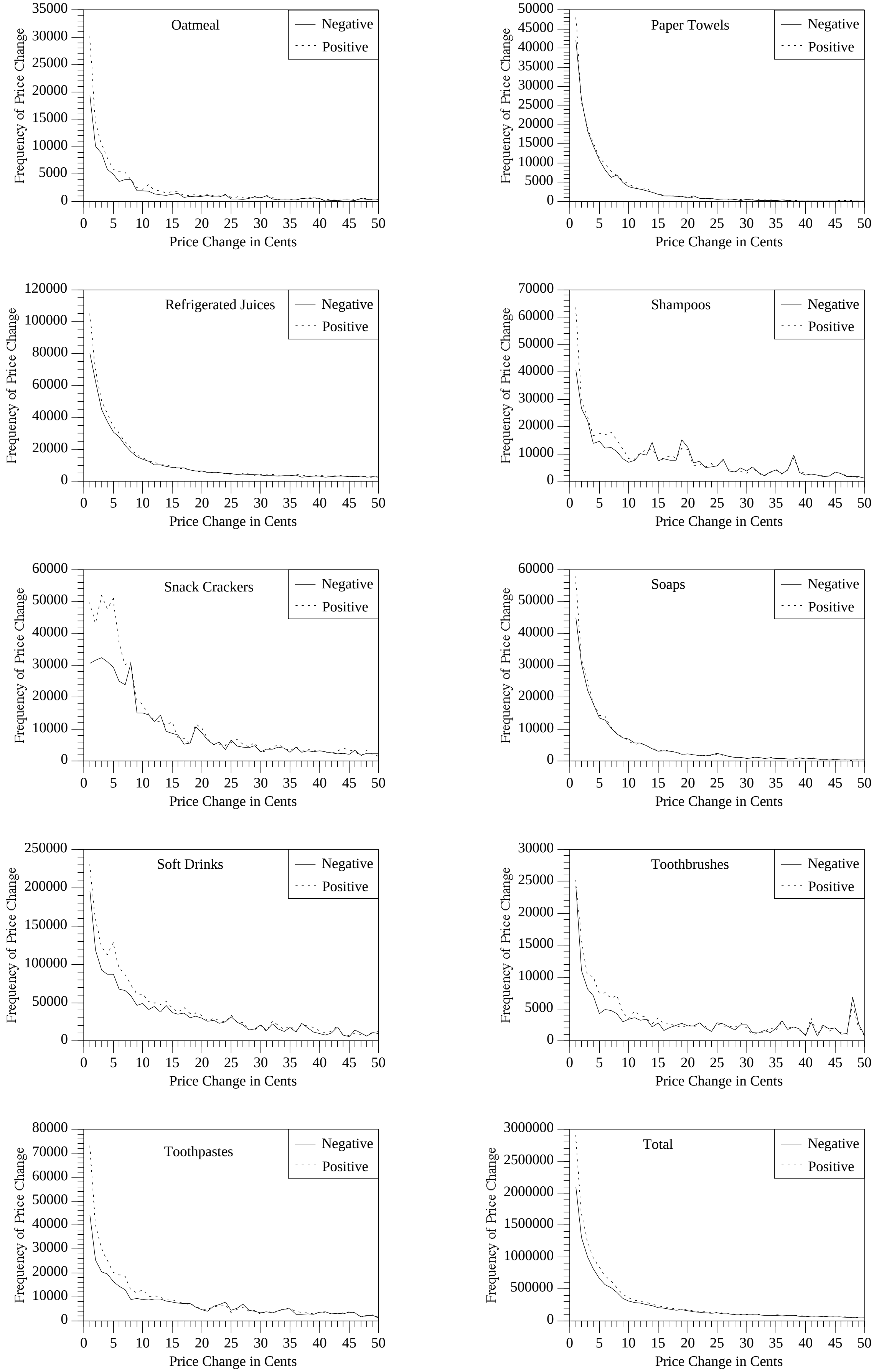


Figure 1.1c. Frequency of Positive and Negative Wholesale Price Changes in Cents by Category

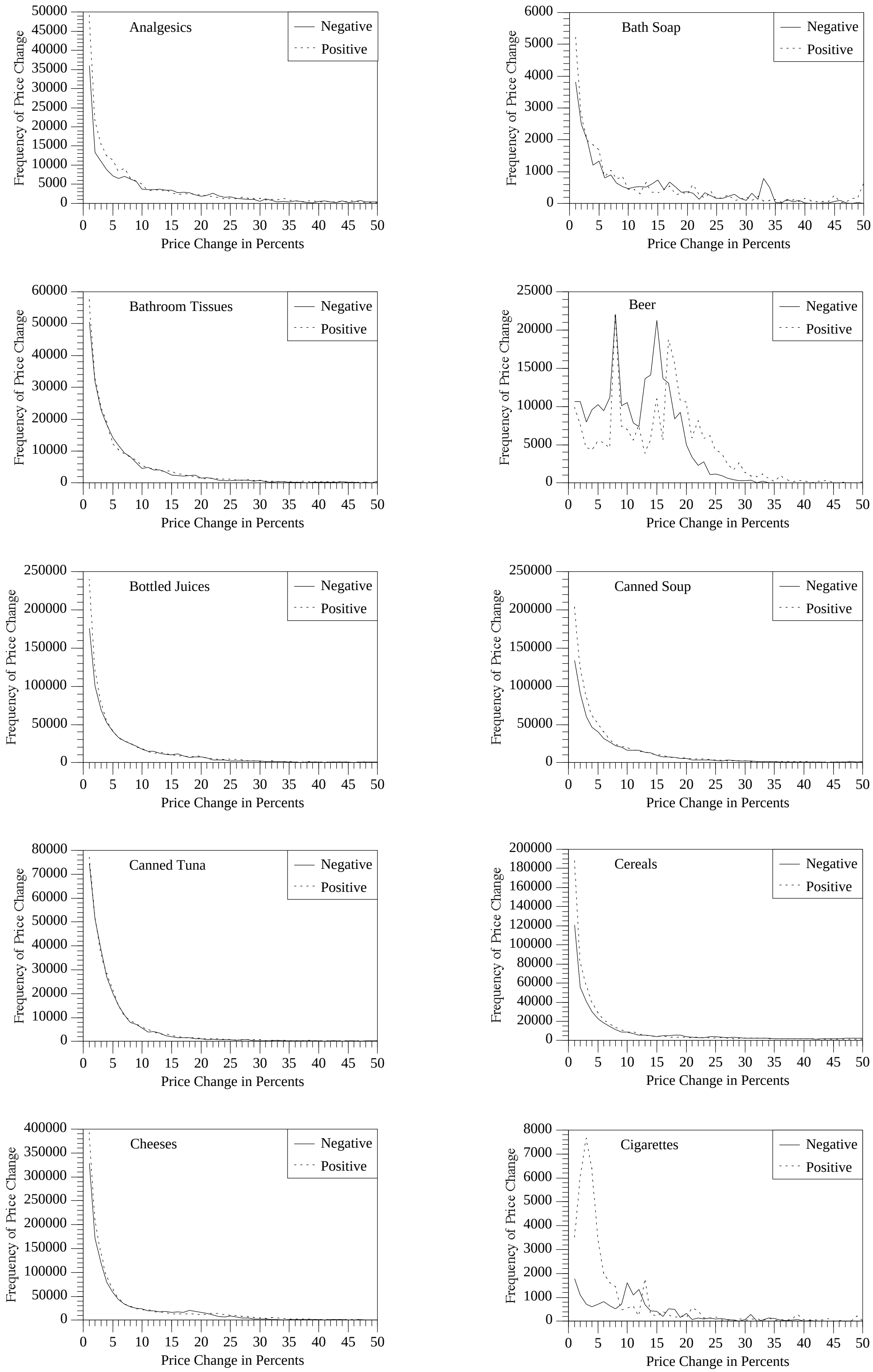


Figure 1.2a. Frequency of Positive and Negative Wholesale Price Changes in Percents by Category

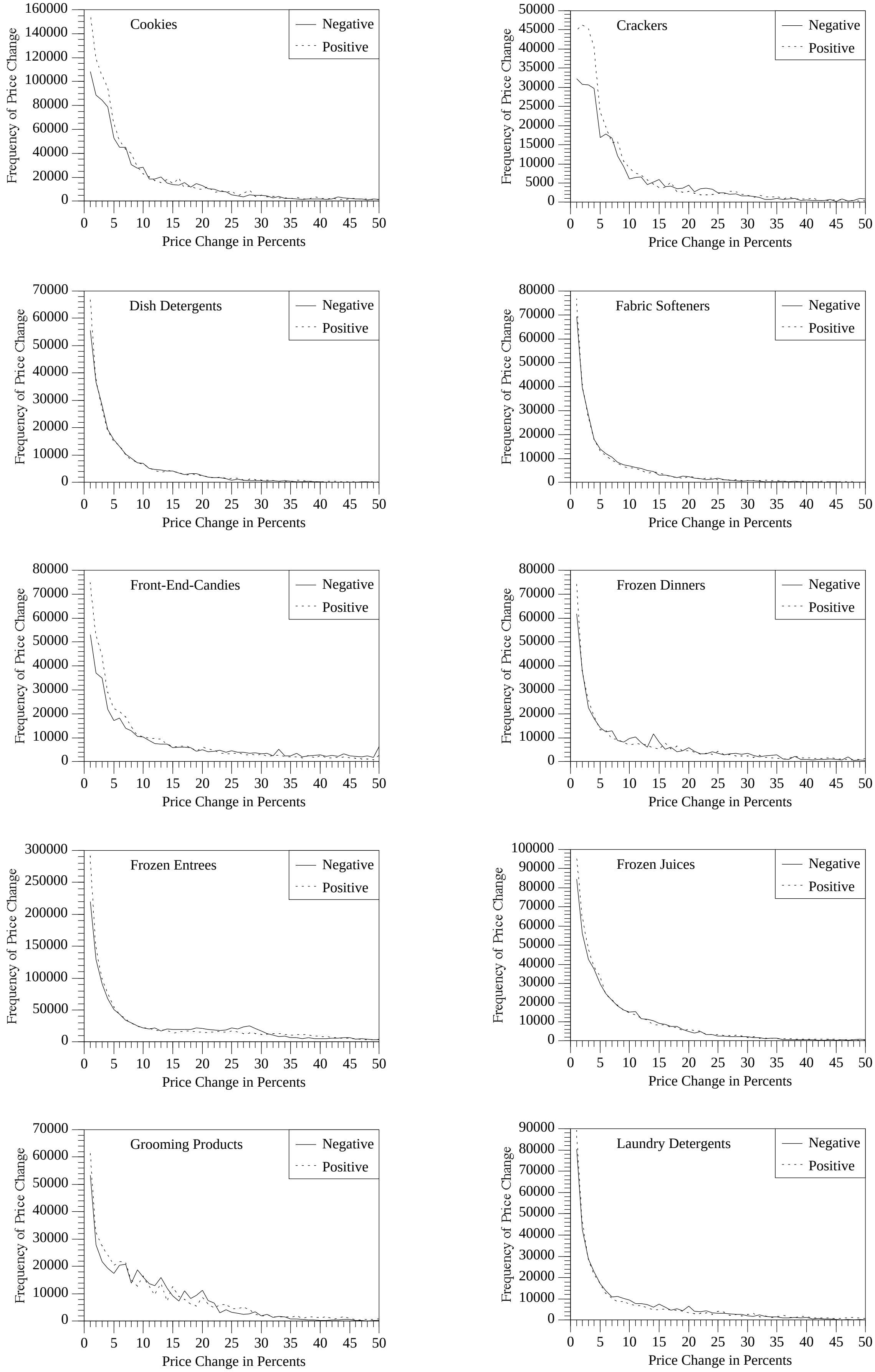


Figure 1.2b. Frequency of Positive and Negative Wholesale Price Changes in Percents by Category

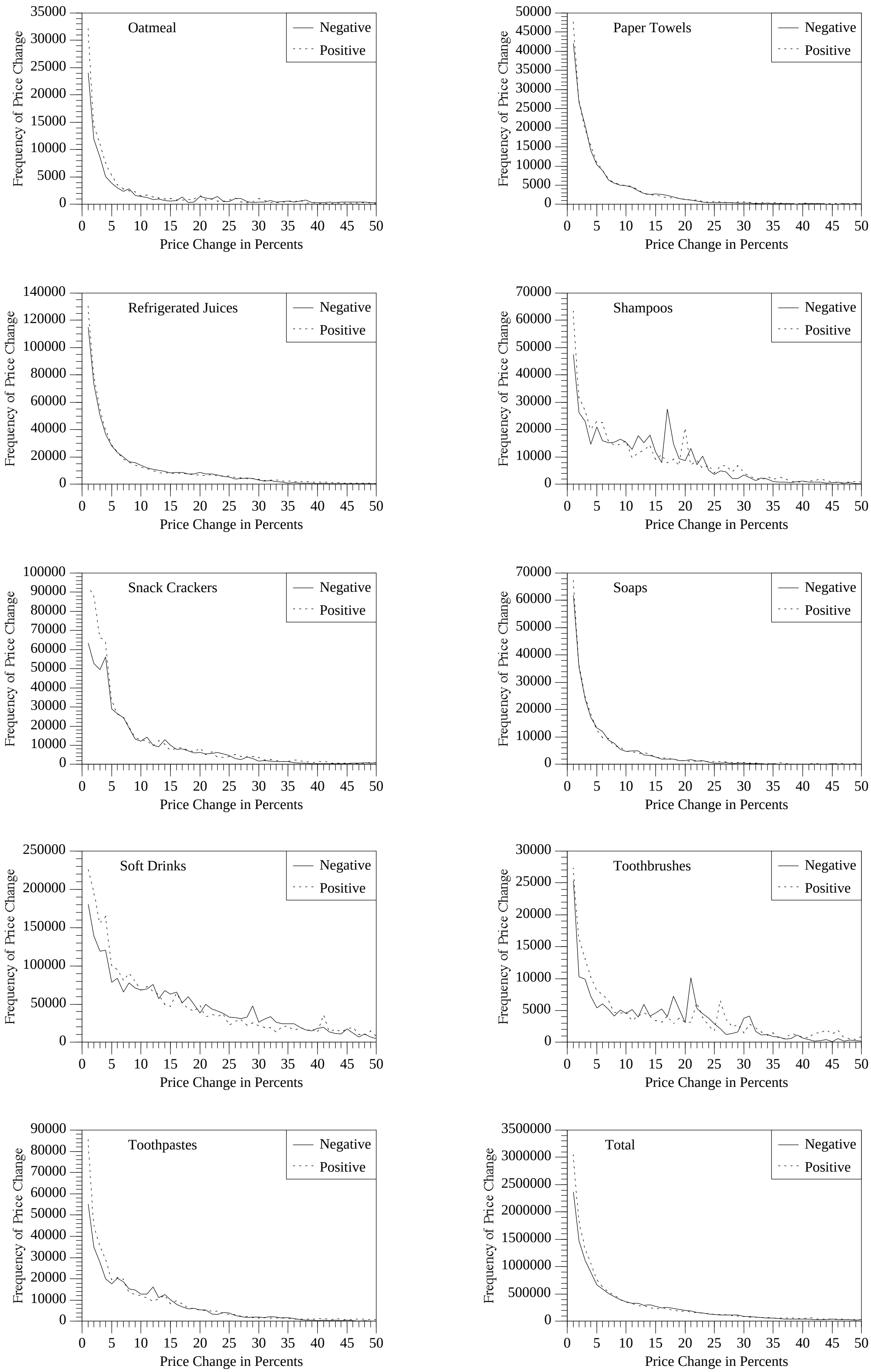


Figure 1.2c. Frequency of Positive and Negative Wholesale Price Changes in Percents by Category

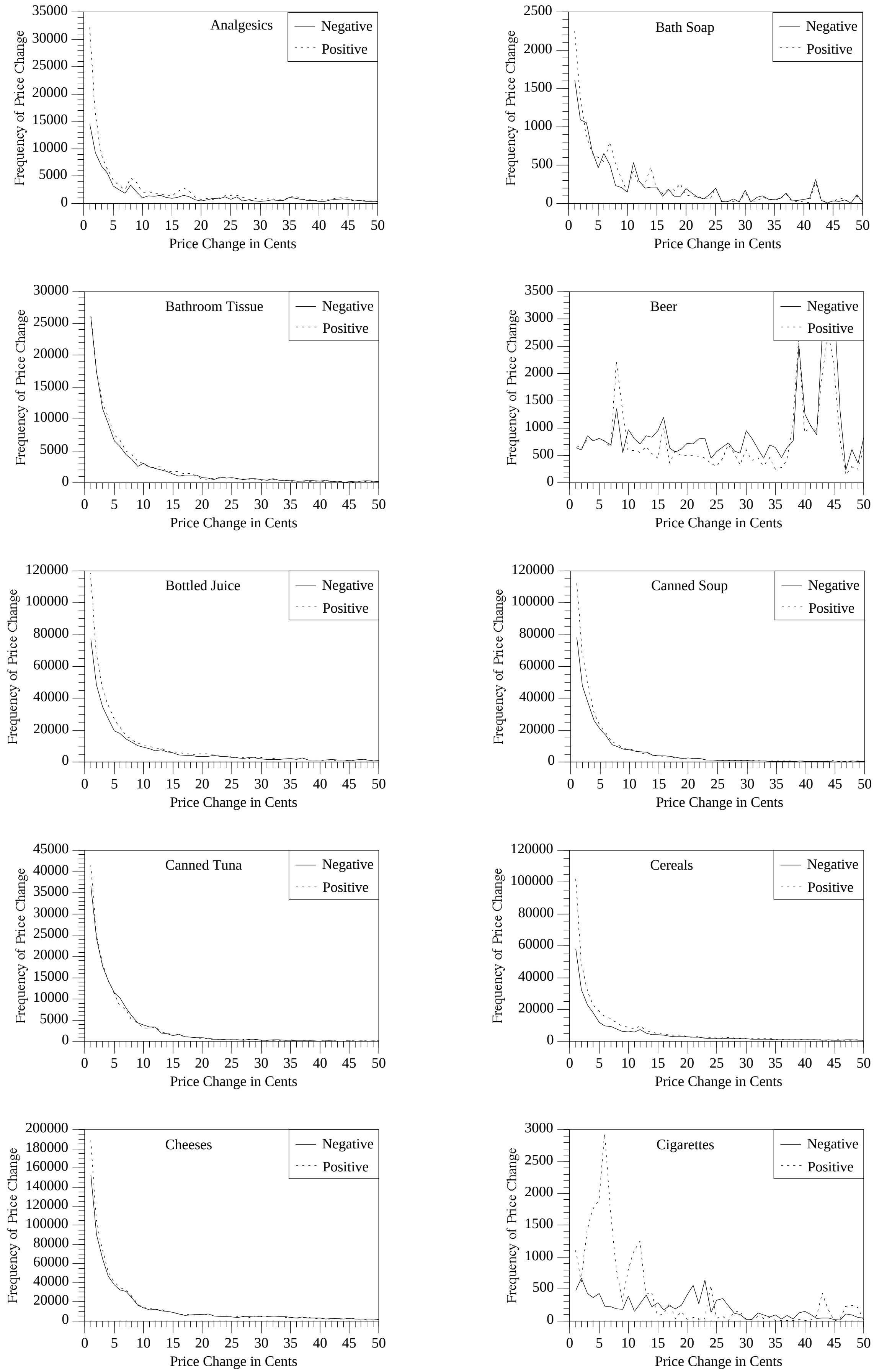


Figure 2.1a. Frequency of Positive and Negative Wholesale Price Changes in Cents by Category, Low/Zero Inflation Period

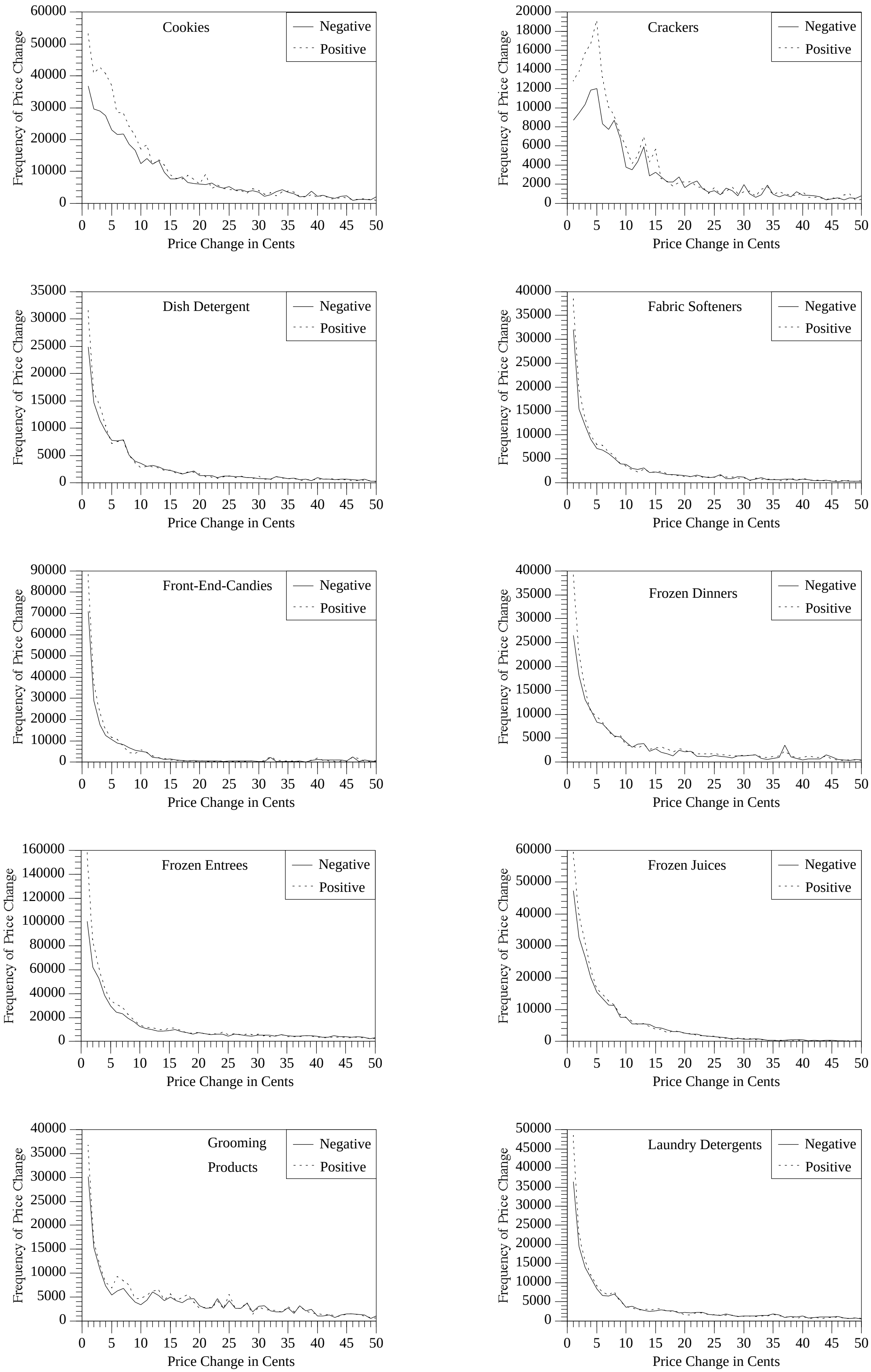
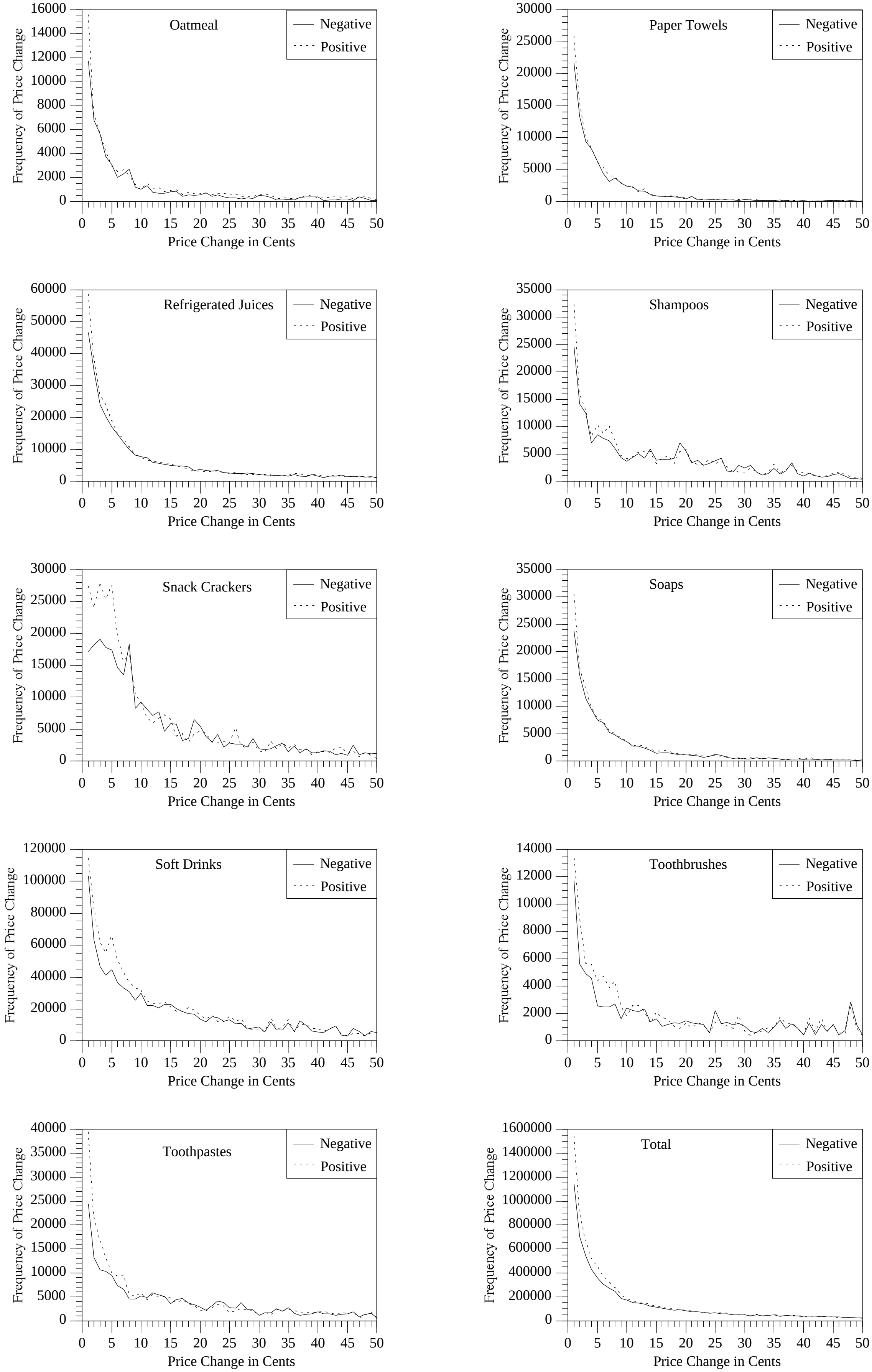


Figure 2.1b. Frequency of Positive and Negative Wholesale Price Changes in Cents by Category, Low/Zero Inflation Period



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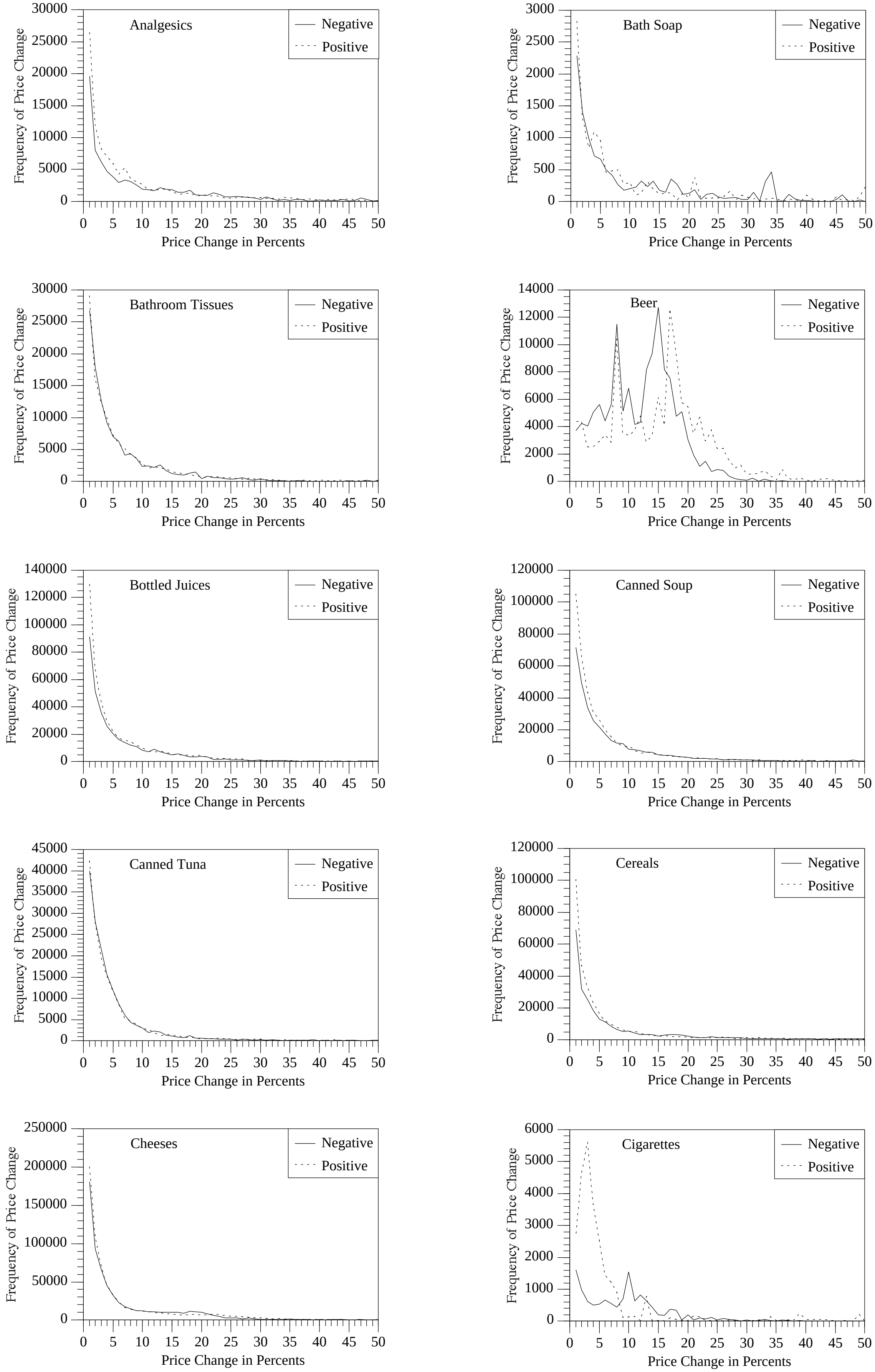
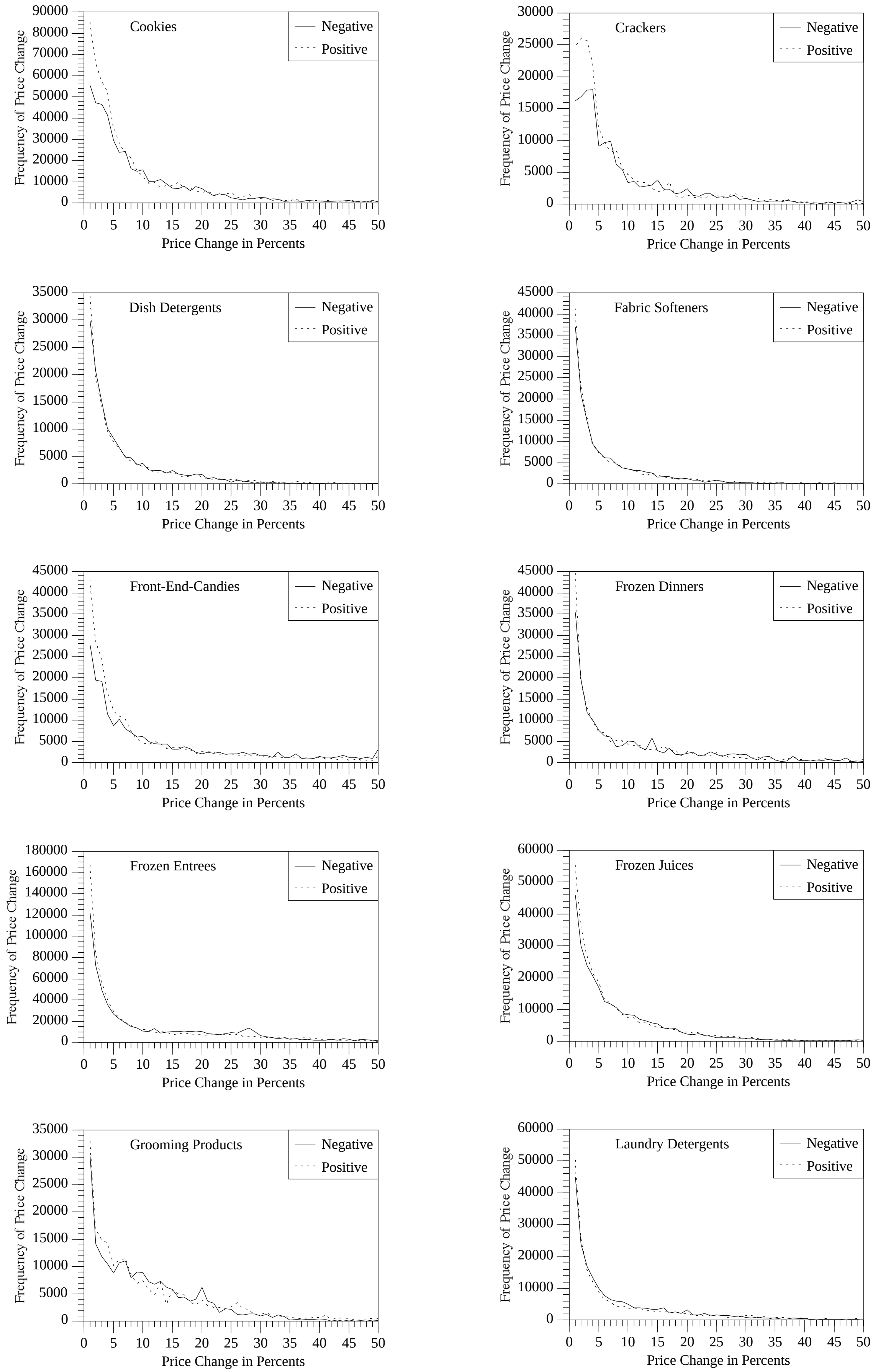


Figure 2.2a. Frequency of Positive and Negative Wholesale Price Changes in Percents by Category, Low/Zero Inflation Period



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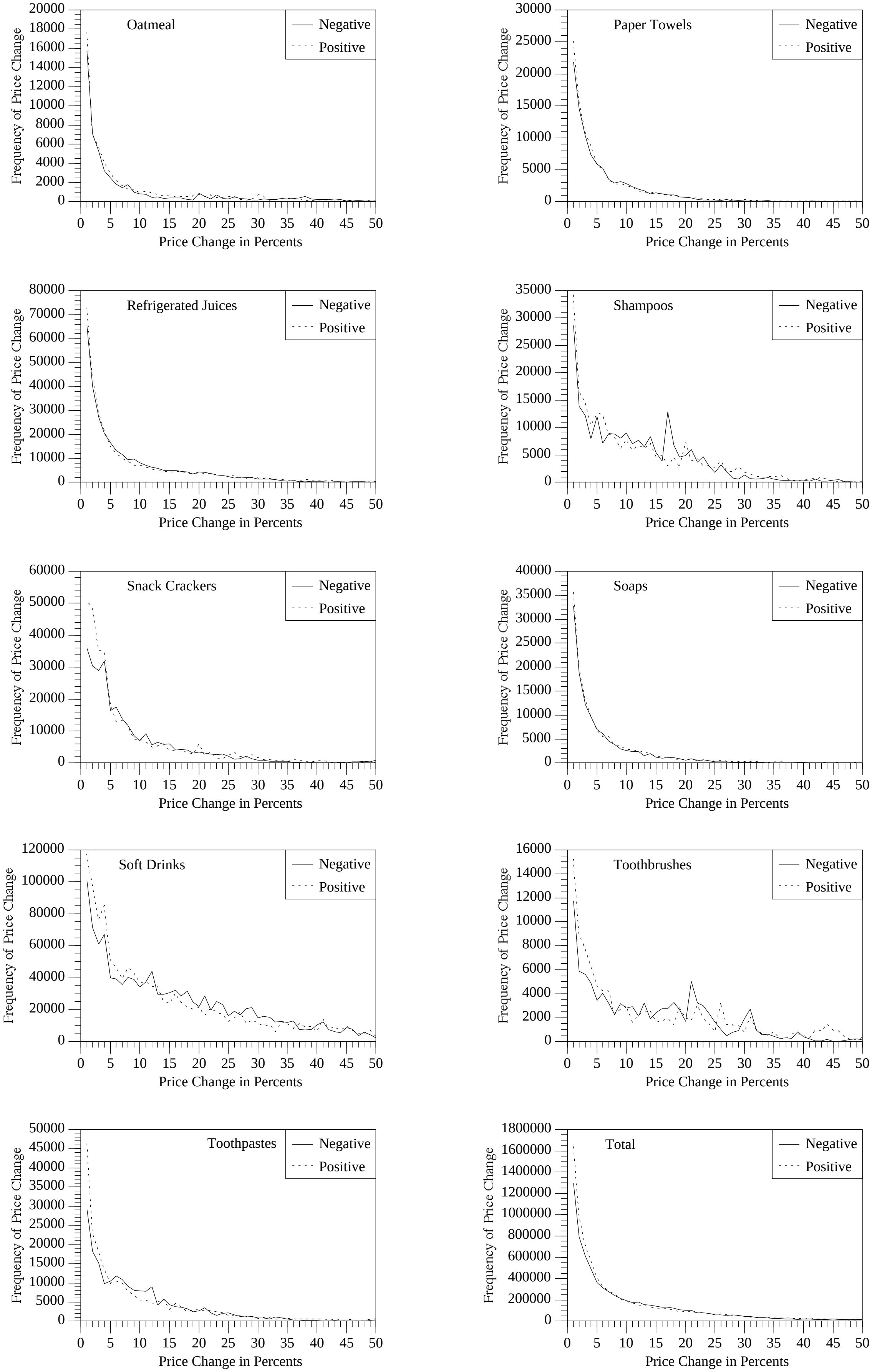

Figure 2.2c. Frequency of Positive and Negative Wholesale Price Changes in Percents by Category, Low/Zero Inflation Period

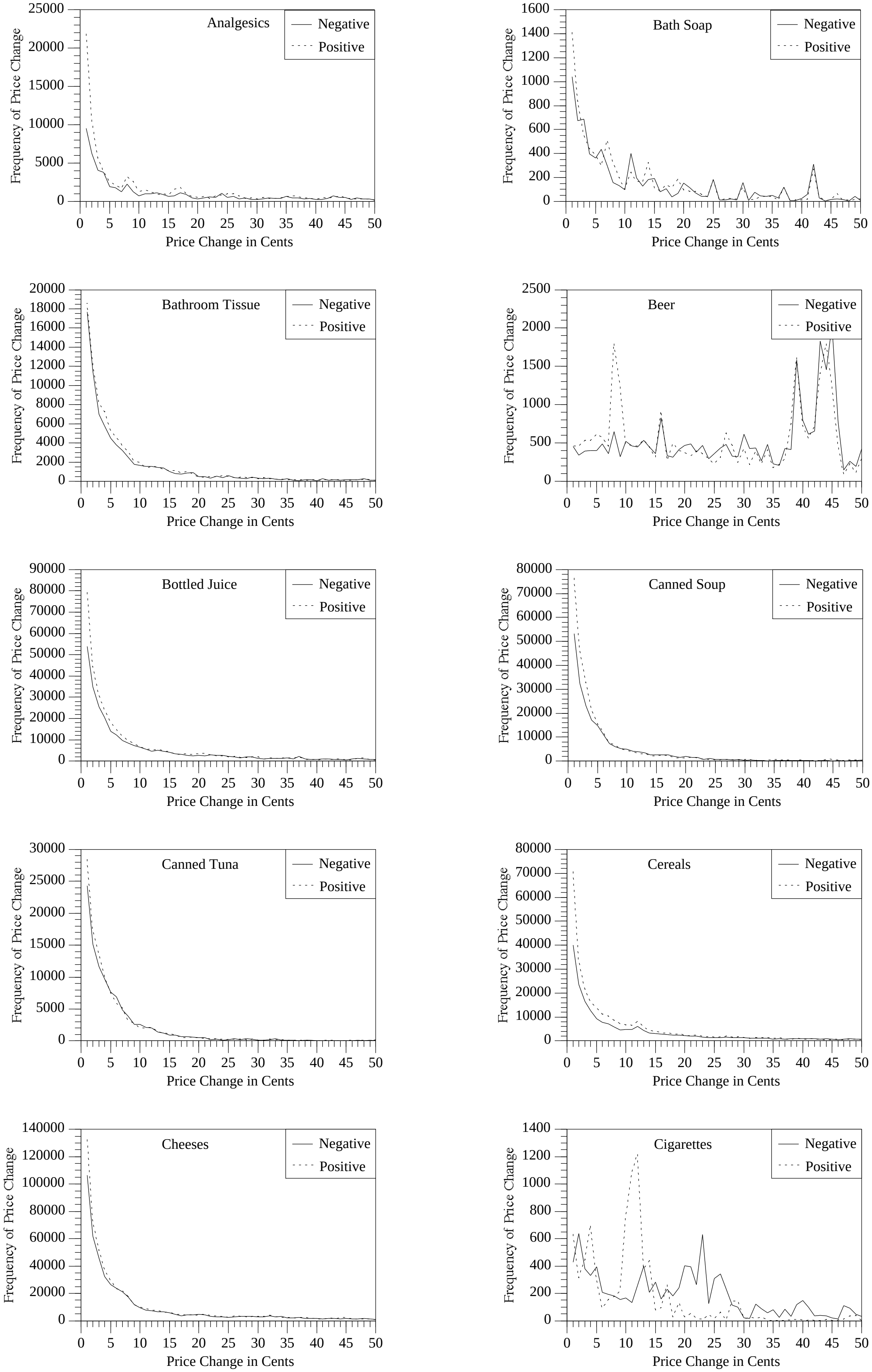

Figure 3.1a. Frequency of Positive and Negative Wholesale Price Changes in Cents by Category, Deflation Period

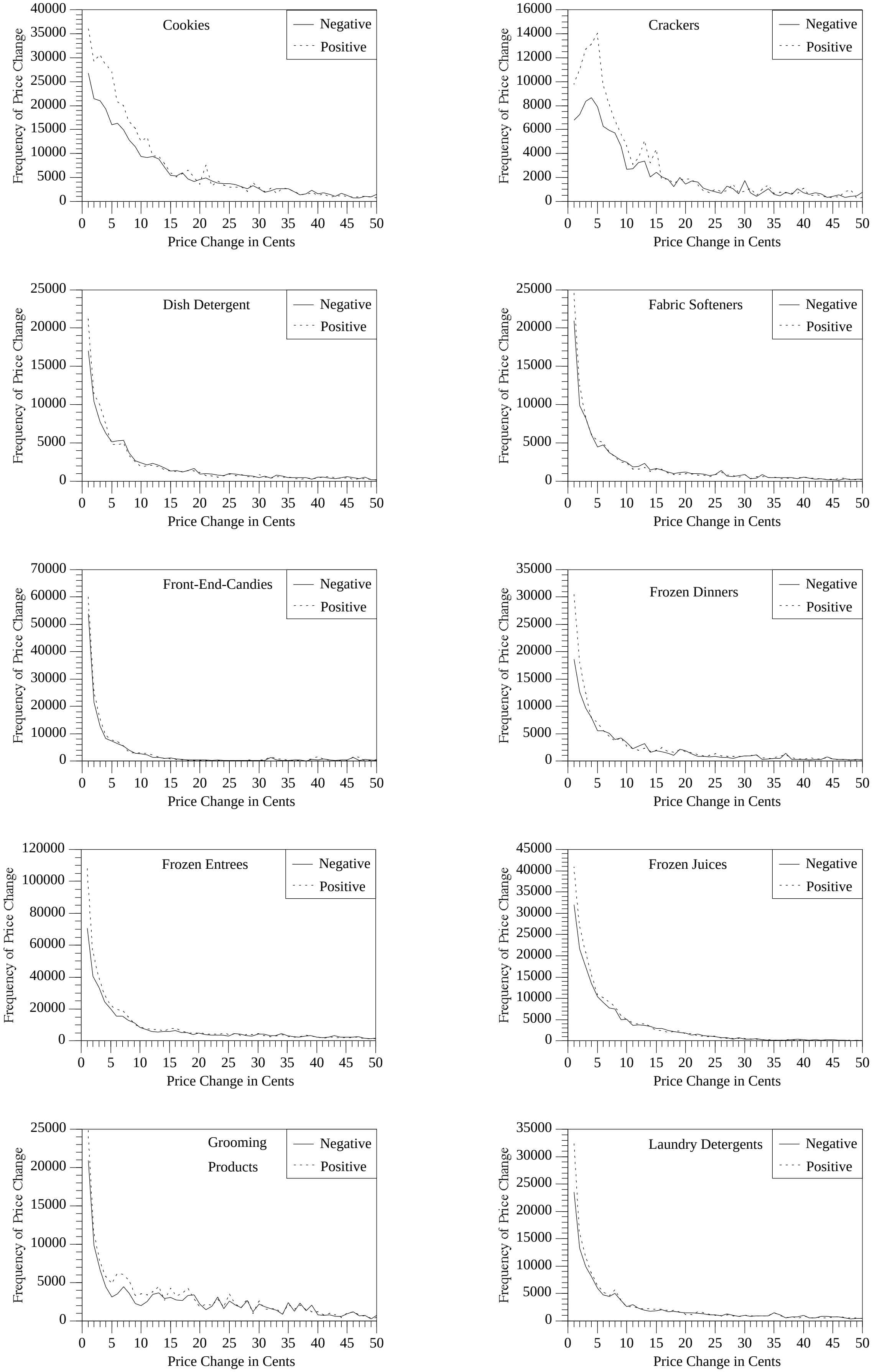

Figure 3.1b. Frequency of Positive and Negative Wholesale Price Changes in Cents by Category, Deflation Period

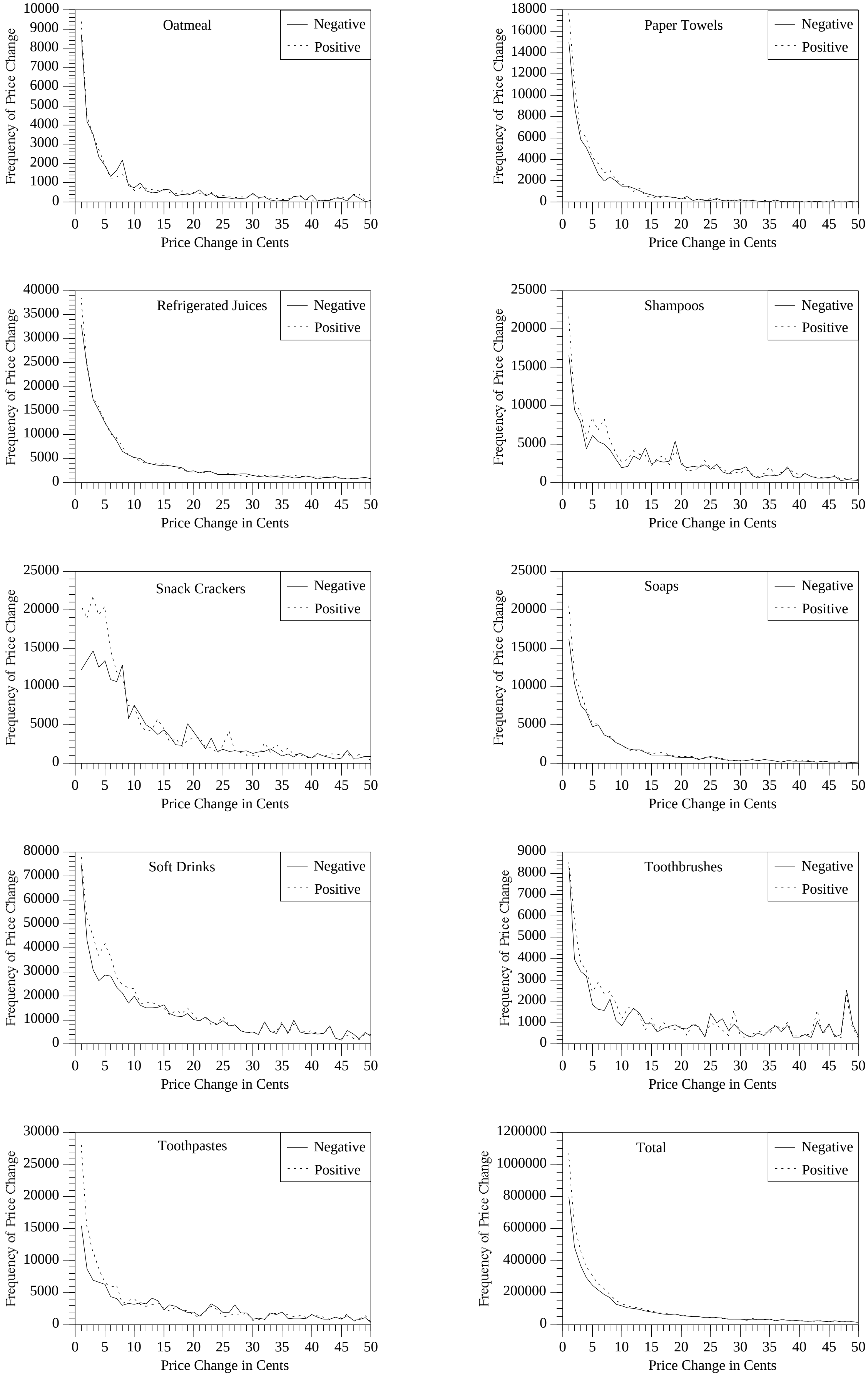

Figure 3.1c. Frequency of Positive and Negative Wholesale Price Changes in Cents by Category, Deflation Period

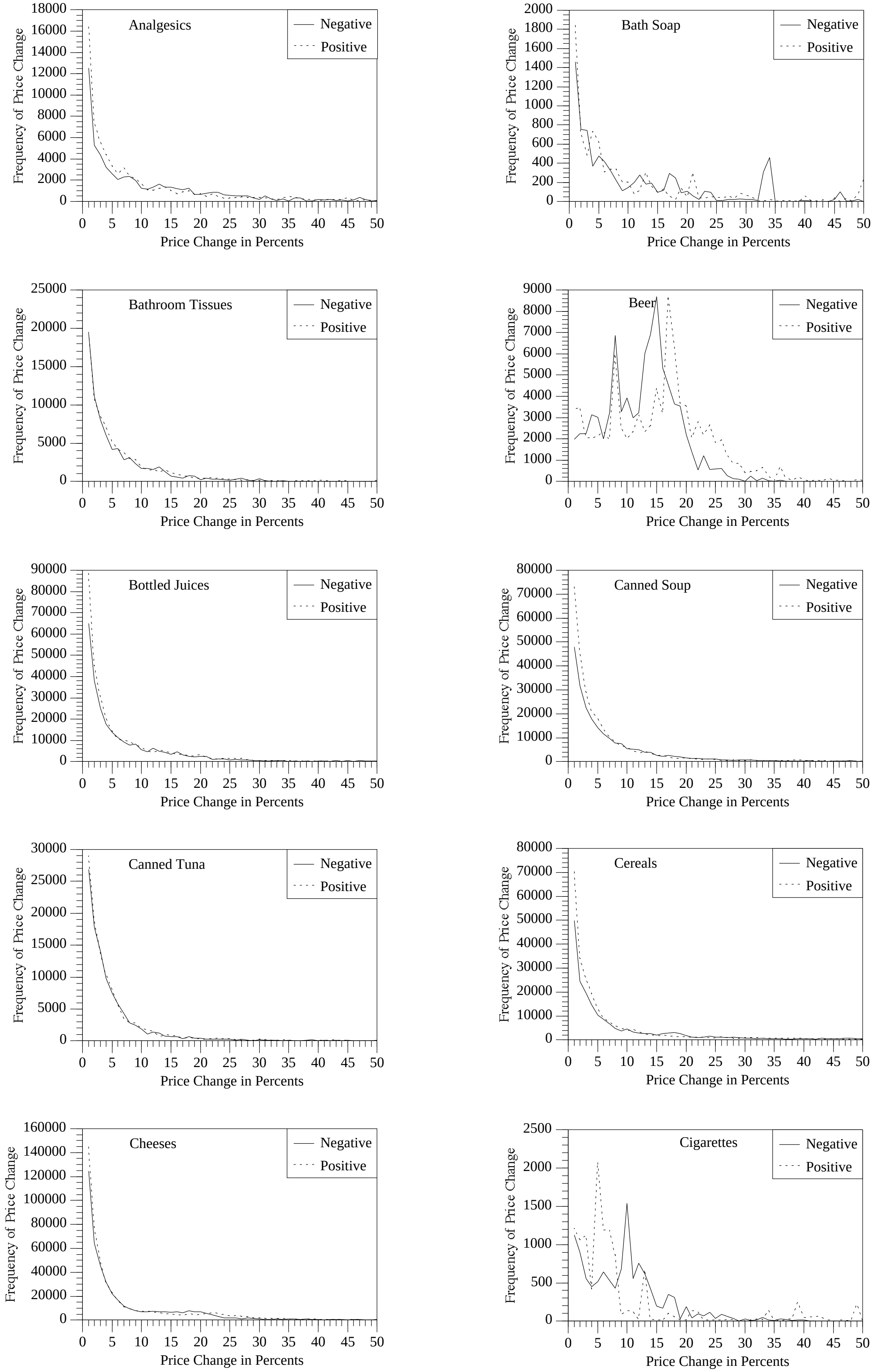

Figure 3.2a. Frequency of Positive and Negative Wholesale Price Changes in Percents by Category, Deflation Period

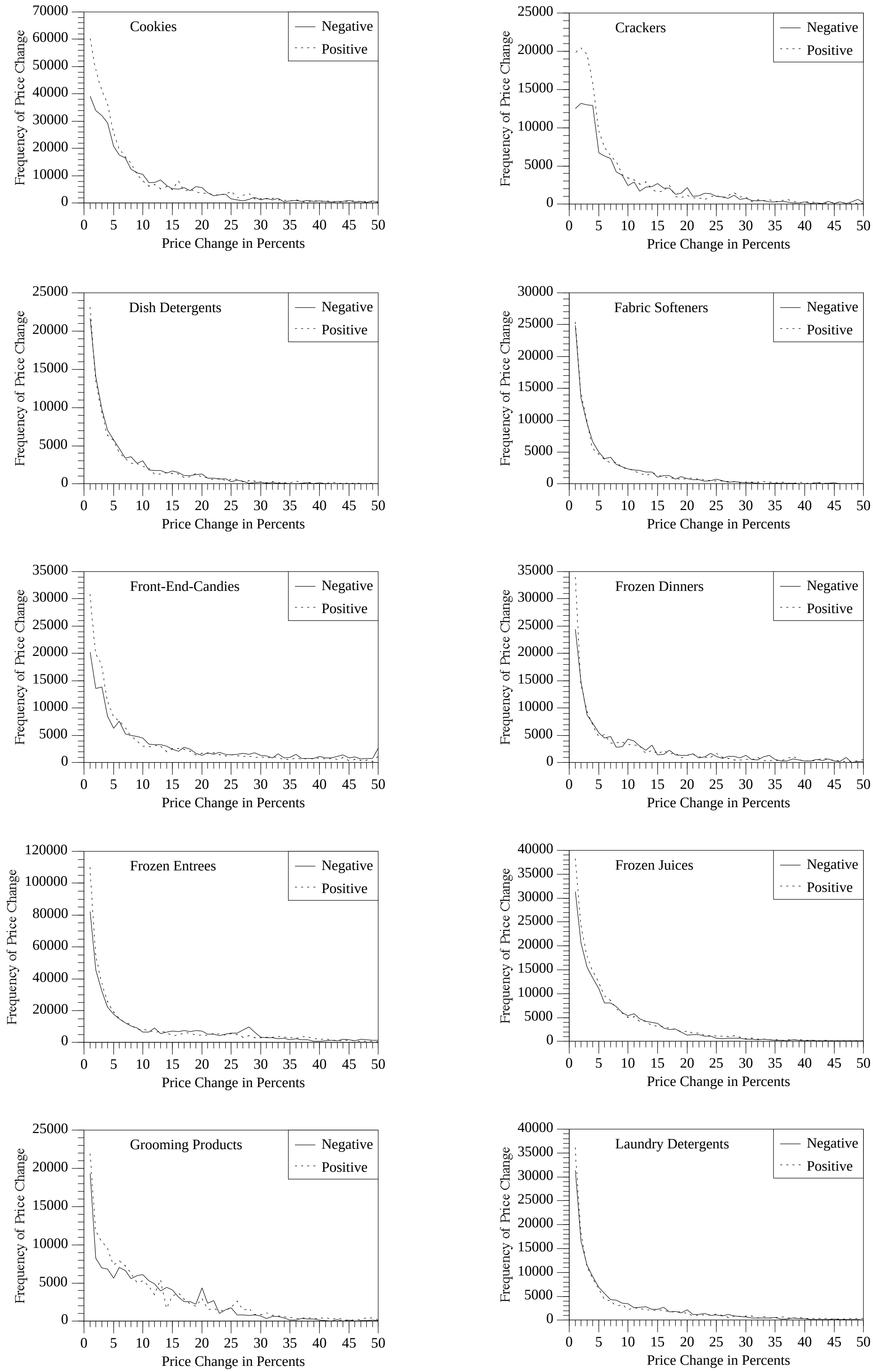

Figure 3.2b. Frequency of Positive and Negative Retail Wholesale Changes in Percents by Category, Deflation Period

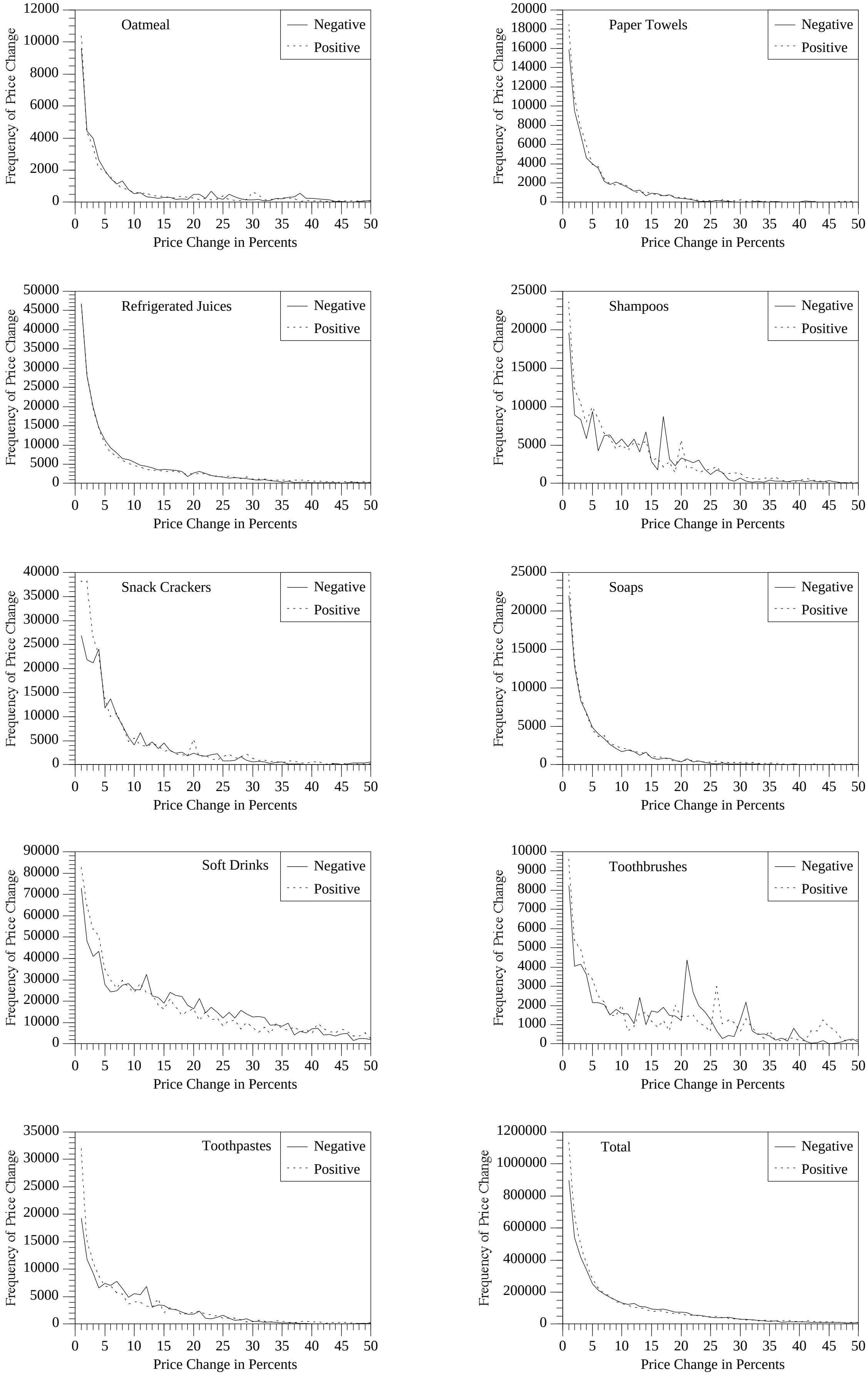

Figure 3.2c. Frequency of Positive and Negative Wholesale Price Changes in Percents by Category, Deflation Period