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STAGGERING AND SYNCHRONIZATION IN PRICE-SETTING: EVIDENCE FROM MULTIPRODUCT FIRMS

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ABSTRACT

Most of the theoretical literature on price-setting behavior deals with the special case in which only a single price is changed. At the retail-store level, at least, where dozens of products are sold by a single price-setter, price-setting policies are not formulated for individual products. This feature of economic behavior raises a host of questions whose answers carry interesting implications. Are price setters staggered in the timing of price changes? Are price changes of different products synchronized within the store? If so, is this a result of aggregate shocks or of the presence of a store-specific component in the cost of adjusting prices? Can observed small changes in prices be rationalized by a menu cost model? We exploit the multiproduct dimension of the dataset on prices used in Lach and Tsiddon (1992a) to explore several of these and other issues. To the best of our knowledge this is the first empirical work on this subject.

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1. Introduction

One of the most important lessons learned from the Fischer-Taylor analysis of staggered contracts is that the mechanism responsible for the long lag in the response of the aggregate price level to shocks in the money supply relies crucially on the assumption of staggered contracts. If agents fully synchronize their actions, the maximum lag of the aggregate response to shocks in the money supply is the length of the contract.

The logic of this argument applies in the price-setting context as well. Under full information, a necessary condition for changes in the aggregate price level to lag behind shocks in the money supply is that the response of price-setters to the monetary shock is staggered over time. Since not all price-setters change their prices simultaneously, each price-setter takes into account that some of his competitors have not yet changed their prices which prevents him from changing his own products' prices to fully accommodate the change in the money supply. Hence changes in the aggregate price level lag behind changes in the money supply.

As shown by Caplin and Spulber (1987), staggering may not be sufficient to generate lags in the response of the aggregate price level, even when price-setters change prices discontinuously. It is, however, always a necessary condition to generate such lag.[1]

In Lach and Tsiddon (1992; hereafter L&T), we analyzed store-level, monthly price data of 26 food products sold in Israel during high inflation periods. Figure 1, reproduced from L&T, shows that price changes do indeed seem to be staggered: in any single month the proportion of price changes is never close either to zero or to one, and it is fairly constant over the 18 months analyzed; it hovers around 30 percent, which is consistent with an average duration of a nominal price quotation of 2.5-3 months.

Note that the staggering referred to above, and in the macroeconomic literature in general, is

[1] See also Ball and Cecchetti (1988), Caballero and Engel (1991, 1993) and Tsiddon (1993).

across decision-makers (price-setters), not across products. Most of the theoretical and empirical literature on price-setting behavior focuses on the single-product case, thus avoiding the conceptual ambiguity in the concept of staggering. Nevertheless, the presence of multiproduct firms raises the possibility that the staggering of price changes occurs across products and not across price-setters.[2] For example, suppose that price-setters sell the same 9 products and change the prices of the first three products in month 1, of the second three products in month 2 and of the last three in month 3. In month 4 they start the cycle again. We will then observe that a third of all prices are changed in each month. The reason is staggering across (groups of) products and perfect synchronization of all price-setters. Of course, the same observed number of changes is obtained when a third of the stores change all 9 prices in month 1, another third does so in month 2, and the remaining third of all stores changes prices in month 3. The reason here, however, is staggering of price-setters in the timing of their price changes accompanied with perfect synchronization of price changes within each store.

This extreme example shows that the same observed data can result from diametrically opposed causes. The problem with Figure 1 is that it does not distinguish between changes in products' prices within a store or across stores. This paper will tackle this issue and shed some light on the forces responsible for staggered price changes. Distinguishing between prices-setters and products' staggering is important for macroeconomic analysis.

Our analysis leads us to conclude that Figure 1 is the result of staggering across price-setters, while price changes of different products are synchronized, although not fully, within the store. That is, the data exhibit across-stores staggering and within-store synchronization in the timing of price changes. This finding validates the assumption of staggered decisions across price-setters made in most of the "sticky prices" literature.

We also think that the existence of within-store synchronization fits better the implications of

[2] Tommasi (1993a) seems to be the first to address this issue.

models of price-setting behavior based on the presence of convex costs of adjusting prices (menu cost models), than those of models based on imperfect information, or those of models based on search equilibrium with no convexities. The following example explains why.

Suppose an aggregate shock arrives at the store -- how will it react? According to signal extraction models, a store will change the prices of all its products in a manner directly related to the size of the shock. According to menu costs models, if the store faces costs of adjusting the price of each product, and if these costs have a store-specific component, then not all stores will necessarily change their prices. Because of this fixed cost component, stores that do change prices will tend to so for most of their products. Furthermore, there is no clear-cut relationship between the size of the price change and the size of the shock. The implications of the last approach are less obvious since, to the best of our knowledge, there exists no model of a multiproduct search equilibrium. It seems likely, however, that a firm in such an equilibrium will respond to an aggregate shock by changing only some of its prices upon impact, postponing other products' price changes for a while. Changing all prices together may generate too strong a signal which is liable to drive consumers away.

This line of reasoning indicates that within-store synchronization in the timing of price changes tends to accord more with menu cost models, where some of these costs are specific to the store (and not to the products), than with the other two explanations.[3]

The observation of "small" price changes in the data is often brought up as evidence against the relevance of menu costs models. In this paper we claim that such small changes can be expected when a multiproduct firm is subject to costs of adjusting prices that have a firm-specific component. In this case, the optimal change in the price of a single product may indeed be small. What should not be observed if store-specific costs exist is all simultaneous price changes in the store being small. Indeed,

[3] Obviously, the three explanations do not contradict one another. In some cases it is useful to consider some or all of these explanations together (e.g., Benabou, 1988).

the data show that the average change within a store is large.

The paper is organized as follows: next section briefly describes the price data. In Section 3, across-stores staggering in the timing of price changes is analyzed. The evidence on within-store synchronization is presented in Section 4. Section 5 investigates the timing of negative price changes. Section 6 interprets the accumulated evidence, and Section 7 deals with the importance of store-specific menu costs from various perspectives. Conclusions close the paper.

2. Description of the data

The data used in this work is a subsample of the data used in L&T, where it is described in detail. The original data set consists of nominal price quotations for 26 food products collected monthly from a sample of stores by the Central Bureau of Statistics (CBS) for the purpose of computing the consumer price index (CPI).[4] That is, for each product we have a panel of prices extending across stores and over time. Alternatively, for each store we have a panel of prices extending over products and over time.

The products in the sample are all homogeneous, did not change substantially either in quality or in market structure, and their prices were not controlled by the government during the period of investigation.

Since part of the focus of the current study is on issues related to the co-movement of prices within stores, we selected 21 products that could be grouped into two broad classes: wines and meat products.[5] Note that each store in our data sells either wine or meat products. None of the stores in our

[4] These are grocery or liquor stores; supermarkets and chain stores are not included in the sample.

[5] Wine products consist of 9 wines and liquors: arrack (anise), white vermouth, liquor, champagne, vodka, red wine, rosé wine, hock wine and sweet red wine. The 12 meat products, including three types of fish, are: fresh beef, frozen goulash, frozen beef liver, fresh beef liver, chicken breast, chicken liver, turkey breast, beefsteak, drumsticks, fish fillet, buri fish and codfish.

sample sell both wines and meat.

The periods for which most of the data are available are 1978-1979, 1981-1982, and the first nine months of 1984, before across-the-board price controls were put first into effect. The data for 1980 and 1983 have disappeared from the CBS archives. The analysis in this paper is restricted to the 1978-1979:6 subperiod, corresponding to a single inflationary step as defined by Liviatan and Piterman (1986), because the price-duration data are less affected by the 1 month truncation introduced by the sampling interval.[6]

The object of study is the occurrence of a price change. In order to take account of round-off errors this event is defined to occur whenever a observed price change exceeds half a percent.

In the latter part of this paper we analyze the within-store dimension of the data. For this to be meaningful we focus on stores selling three or more products. The upper graph in Figure 2 plots the number of stores meeting this requirement by product class. Twice as many stores sell meat than wines, and the number of stores is stable over time.[7] The number of products, averaged over stores, is given in the lower graph: it fluctuates between 5.5 and 6 products with a standard deviation of 2-2.5 products. There is not much variation over time in these averages. There is variation, however, in the number of products actually sampled across stores -- there are relatively more meat stores selling fewer products than liquor stores, and only a few meat stores sell over 9 products.

3. Across-stores staggering

As mentioned in the Introduction, a necessary condition for an effective monetary policy is that not all price-setters should change their prices simultaneously in response to a monetary shock. If this is so, each price-setter takes into account that some of his competitors have not yet changed their prices

[6] During this period the mean inflation rate was 3.9 percent per month, with a standard deviation of 1.9 percent. The median rate was 3.5 percent per month.

[7] In L&T we showed that even though there were some changes over time in the identity of the stores, there is a sizable core of stores that remained in the sample for long periods of time.

which, in turn, prevents him from changing those of his own products to fully accommodate the monetary shock. Hence, the aggregate price level may not respond completely and immediately to unexpected changes in monetary policy.

This lack of simultaneity is termed "across-stores staggering". The term refers to staggering in the timing of price changes across different stores for a given product. In most macroeconomic models (e.g., Fischer, 1977), across-stores staggering implies more than mere lack of simultaneity; It also embodies the notion of "regular cyclicity" in the response of price-setters to a shock. One group of price-setters is first to change prices, followed by another group of different price-setters; at some point in time, however, before the second group acts again, the first group of price-setters changes its prices a second time.[8] Our data are uniquely suited to check the extent to which these phenomena prevail. This is the purpose of this section.

At this stage let us clarify the relationship between statistical independence across stores and staggering. Let $X_{ijt} = 1$ indicate that store i changed the price of product j in month t. Otherwise, $X_{ijt} = 0$. Obviously, the timing of price changes is correlated across stores, implying that the $\{X_{ijt}\}$ process exhibits some form of cross-sectional dependency (across stores i). The critical point is that this correlation may result because of the stores' response to factors common to all stores (e.g., to an increase in the aggregate rate of inflation), and not because of strategic behavior. In fact, given that our data are composed of small grocery stores located all over the country (we do not sample supermarkets), this is not a bad assumption. Hence the assertion that some stores act on the premise that some of their competitors have not yet changed their prices is not interpreted literally as "neck-to neck" competition. Letting Z_t denote all the common factors alluded to above we assume that conditional on Z_t the probability of store i changing the price of some product is not affected by what store k does or did.

[8] A unique exception in this context is Calvo (1983). While Calvo's model is very useful for understanding the dynamics of inflation, its empirical inadequacy at the micro level has been pointed out by Taylor (1983).

That is, conditional on $\{Z_t\}$, the process $\{X_{it}\}$ is independent across i. Hereafter, independence across stores refers to conditional independence.

This section is divided into three parts, each presenting empirical evidence on different features of across-stores staggering in the timing of price changes.

A. <u>Proportion of price changes</u>

The first step is to examine, for each product, the time series of the proportion of stores that changed prices. Simultaneity or lack of staggering implies that stores either change their prices together or do not, i.e., that the observed proportions are close to one or to zero.

Figure 3 presents such a time series for the 17 months between February 1978 and June 1979, for each product. At first glance, the proportion of stores changing prices is well below 1 in all months, with the exception of November 1978. The requirement that these proportions be above zero is also satisfied though to a lesser extent. Omitting the November 1978 observation, meat products do not exhibit much variability over time compared to wines. Wines, on the other hand, display a quite regular seasonal pattern with a much lower proportion of stores changing prices during the first half of the year.

In a stationary inflation environment a store following an (S-s) pricing policy is expected to change its prices by the same amount every δ months (δ being determined by the parameters of the inflation process and profit function (Sheshinski-Weiss; see 1992).[9] What does this imply for the observed proportions of stores changing prices? If stores are expected to change prices every δ months, and there is sufficient heterogeneity in the initial conditions, then after a long enough number of months, the proportion of stores changing prices every month should stabilize around $1/\delta$. The horizontal dotted line in each panel of Figures 4 and 5 is $1/\delta$, where δ is the average duration of a price quotation taken

[9] In expectations, the store's policy is observationally equivalent to a time-dependent policy.

from Table 4 in L&T.[10] The "fit" seems to be much better for meat products than for wines.

B. Simultaneous price changes

The issue of staggering can be tackled from another angle by asking: how many stores change prices simultaneously? When store i changes the price of product j during month t, M_{ijt} other stores are doing the same. Tables A1 and A2 in the Appendix show the grand mean $M_{i..}$, M_{ijt} averaged over months and products sold by store i, for each store i (column 1). Column 2 shows M_{ijt} divided by the number of competitors, the number of stores selling product j at t minus 1, also averaged over months and products. For example, store 1 in Table A1 changes the price of a typical wine product simultaneously with 7.3 other stores on average. (45 percent of its competitors). Summary statistics of these tables are presented in Table 1.

Table 1: Simultaneous Price Changes

Summary Statistics of Tables A1 and A2

		MEAN	MEDIAN	STD	MIN	MAX
WINES	$M_{i..}$	6.90	6.32	2.50	2.83	14
WINES	Share	0.42	0.40	0.14	0.20	0.87
MEAT	$M_{i..}$	15.24	17.31	4.66	6.8	23.4
MEAT	Share	0.56	0.57	0.06	0.37	0.71

Note: See notes to Table A1.

[10] Note that the average duration was estimated from data on positive price changes only. This may be more appropriate for our purposes. The occurrence of negative price changes represents only 12 percent of the total number of observations.

When a store selling wines changes one of its prices it usually does so together with 7 other stores (42 percent of its competitors) on average. These figures are quite representative: 62.5 percent of the stores change price simultaneously with 5-9 other stores; 50 percent of the stores change prices at the same time that 32-52 percent of their competitors do so. Most stores selling meat products usually change prices simultaneously with 56 percent of their competitors; the interquartile range is only 6 percent.[11]

The preceding analysis indicates that the proportion of stores is away from the zero-one boundaries in general; furthermore, from the point of view of the individual store, a change in prices does not indicate that all of its competitors follow suit, even though a sizable share of them do.

C. Regular cyclicity

Another characteristic of across-stores staggering is not captured either by the observed proportions of price changes or by the number of simultaneous moves. As the opening paragraph of this section suggested, having the same group of firms change prices every month during the first, say, six months, while another group does so during the second part of the year, is not the kind of staggering economists have in mind when analyzing price dynamics; it does not conform with the notion of regular cyclicity. This is also not the behavior implied by the (S-s) model of price changes. Staggering embodies a notion of regular cyclicity.

The "perfect" across-stores staggering is one in which, in response to a monetary shock, a different $1/\delta^{th}$ of all stores changes prices every month. After δ months all stores have responded to the shock and the cycle can start again. Hence, the perfect time series of $X_{\bar{q}t}$ is composed of ones every δ months and zeros everywhere else.

[11] These figures are averages and should be treated with caution. For each store there is variation both in the number of months sampled within each product and in the number of products sold.

We examine the X_{ijt} time series for each store i and product j. There are potentially 360 and 1,080 such series for wines and meat products respectively.[12] We focus on the occurrence of consecutive price changes; a pattern not consistent with across-store staggering in the timing of price changes. For our purposes, this is more informative than descriptive statistics on the duration of price quotations for each store. We count the number of times prices were observed to change consecutively at least twice, at least three times, and so on. The counting is done for each store separately over all the products sold by the store and over the months for which data form it are available (the maximum being 17 months per product). Since the number of products sold and the number of months for which there are data vary over stores, we divide the <u>observed</u> number of K consecutive price changes by the <u>potential</u> number of K consecutive price changes, for $2 \leq K \leq 17$. The entries in Tables A3 and A4 can thus be interpreted as unconditional probabilities of observing K consecutive price changes.[13] Table 2 presents summary statistics.

[12] For example, there are 40 distinct stores selling some of the 9 wine products. Potentially there are 360 series, but a non-negligible number of them are missing since most stores do not sell all 9 products.

[13] We count non-overlapping spells of consecutive price changes. For example, a spell of 4 consecutive changes is counted only once as a spell of 4 and not as 3 spells of 2 or 2 spells of 3. The qualifier "at least" is important. Since our data are censored from both right and left, there are many instances in which a spell of two consecutive price changes is preceded or followed by a missing value. The censoring results either from a store not being included in the sample in a particular month or from the store having run out of the product at the time of sampling.

The potential number of K consecutive price changes is derived as follows: first, we identify the spells of L consecutive observations on X_{ijt}, $2 \leq L \leq 17$. The reason for having spells of varying size is the presence of lots of missing values in the X's. Next, for each spell of length L we count the number of possible ways K non-overlapping consecutive price changes, $X_{ijt} = 1$, can occur. We then sum over all observed spells. For example, store 1 sells 7 wine products. The number of times two consecutive price changes occurs is 2, 0, 0, 1, 0, 0 and 1 respectively. The observed number of two consecutive price changes is, therefore, 4. We identified 2 spells of 7 consecutive non-missing X's (in products 1 and 9), 3 spells of 6 (in products 2, 6 and 7), 1 spell of 5 (in product 8), one spell of 3 (in product 3) and one spell of 2 (in product 3). The potential number of two consecutive price changes is, therefore, 14. The C2 entry for store 1 is 4/14 = 0.286.

Table 2: Probability of a Consecutive Price Changes

Summary Statistics of Tables A3 and A4

		C2	C3	C4	C5	C6	C7	C8	C9
MEAN	W M	0.083 0.189	0.026 0.105	0.003 0.103	0.002 0.048	0 0.021	0 0.016	0 0.020	0 0.030
MEDIAN	W M	0.05 0.176	0 0.097	0 0.062	0 0	0 0	0 0	0 0	0 0
PERCENTAGE OF ZEROS	W M	41.0 10.1	66.7 35.2	94.9 45.5	94.9 67.1	100 84.5	100 89.0	100 92.5	100 91.1
STD	W M	0.119 0.137	0.045 0.109	0.013 0.150	0.010 0.091	0 0.058	0 0.053	0 0.115	0 0.131
MAX	W M	0.571 1.000	0.200 0.500	0.074 1.000	0.05 0.500	0 0.333	0 0.333	0 1	0 1

Note: The mean probability for C10-C17 is less that 0.01; see also notes to Table A3.

From Table A3 we see that close to 40 percent of the liquor stores never spread out a change in the price of any of its products over two or more months (C2-C17 have zero entries in 15 stores). The estimated probability of spreading out a price change over two or three consecutive months is quite low (except for stores 1, 2 and 9). The mean probability, averaged over stores, is 8.3 percent, while the median probability is only 5 percent, reflecting the large number of zero values. Even without their standard errors, these estimates suggest that consecutive price changes are not a prevalent phenomenon in liquor stores.

Table A4 indicates that most stores selling meat products experienced two, three and even four consecutive price changes at least once. Although infrequent - the mean probability is never above 19 percent - these events do occur often enough to warrant a different characterization than liquor stores. Note that a non-negligible number of stores do have 5 or more consecutive price changes. Unlike liquor stores, the notion of across-stores staggering in the timing of price changes finds less support in the meat-products market. We return to this point at the end of the section.

A different perspective on the issue of regular cyclicity is also instructive. A modest requirement for staggering to occur is that stores alternate their decisions to change prices, i.e., that stores that change prices in the current month did not do so the month before and, conversely, stores that changed prices last month do not do so this month.[14] Note that this behavior is not sufficient to generate staggering. If stores do behave this way, and if there is sufficient heterogeneity in the stores' initial conditions, across-stores staggering will be occur. Otherwise, the result may be a situation where all stores do indeed alternate their price changes but do so in a synchronized fashion. Note, however, that the latter theoretical possibility is not supported by our findings in the previous subsections.[15]

A simple 2x2 contingency table with two rows for the values of X_{ijt-1} and two columns for the values of X_{ijt} summarizes this information for each store-product-month observation. Assuming that X_{ijt} is (conditionally) independent and identically distributed across stores allows us to aggregate the tables over stores.[16] This still leaves us with 17x21 tables for each product-month combination. Assuming that the distribution of X_{ijt} is time-invariant during the 17 months reduces the information to 21 2x2 tables (9 wines and 12 meat products). Table 3 presents these contingency tables.

[14] An empirical check of this assertion is meaningful only if stores are sampled more often than the frequency of price changes which is the case in the 1978-1976:6 period.

[15] To see this consider a case where the probability of a price change at t given X_{ijt-1} is 0 if X_{ijt-1} = 1 or 1 if X_{ijt-1} = 0. Stores wait one month between price changes. Suppose there is heterogeneity in that half the stores start with a price change. Then in any two consecutive months there will always be different halves of the stores changing price. If there is no initial heterogeneity, all stores change prices every other month. Hence, alternating behavior is not sufficient to generate across-stores staggering in the timing of price changes. In this context, Caballero and Engel (1991, 1993) show that if the number of stores selling the product is constant over time, if the conditional probability of changing the price is the same across stores and is time-invariant, and if the stores behave independently of each other, in the limit, the proportion of stores changing price is constant over time.

[16] Note that this assumption allows for heterogeneity in the size of the price change.

Table 3: 2x2 Contingency Tables
Wine Products

	Product W1			Product W2			Product W3		
Row Percent Column Percent	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total
X_{t-1}=0	0.74 0.78	0.26 0.72	228	0.76 0.79	0.24 0.81	193	0.79 0.81	0.21 0.87	163
X_{t-1}=1	0.68 0.22	0.32 0.28	71	0.78 0.21	0.22 0.19	50	0.86 0.19	0.14 0.13	35
Total	217	82	299	186	57	243	159	39	198

	Product W4			Product W5			Product W6		
Row Percent Column Percent	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total
X_{t-1}=0	0.78 0.80	0.22 0.73	138	0.77 0.80	0.23 0.79	209	0.76 0.78	0.24 0.75	214
X_{t-1}=1	0.71 0.20	0.29 0.27	38	0.75 0.20	0.25 0.21	53	0.73 0.22	0.27 0.25	63
Total	135	41	176	200	62	262	208	69	277

	Product W7			Product W8			Product W9		
Row Percent Column Percent	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total
X_{t-1}=0	0.76 0.77	0.24 0.88	190	0.76 0.77	0.24 0.75	202	0.75 0.79	0.25 0.88	264
X_{t-1}=1	0.88 0.23	0.13 0.12	48	0.74 0.23	0.26 0.25	62	0.85 0.21	0.15 0.12	62
Total	186	52	238	199	65	264	252	74	326

Table 3 (cont.): 2x2 Contingency Tables
Meat Products

	Product M1			Product M2			Product M3			Product M4		
Row Percent Column Percent	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total
X_{t-1}=0	0.47 0.49	0.53 0.39	284	0.66 0.64	0.34 0.53	417	0.48 0.47	0.52 0.49	130	0.39 0.39	0.61 0.43	83
X_{t-1}=1	0.37 0.51	0.63 0.60	368	0.55 0.36	0.45 0.47	280	0.50 0.53	0.50 0.51	139	0.43 0.61	0.57 0.57	117
Total	269	383	652	431	266	697	131	138	269	82	118	200

	Product M5			Product M6			Product M7			Product M8		
Row Percent Column Percent	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total
X_{t-1}=0	0.52 0.56	0.48 0.53	141	0.44 0.46	0.56 0.43	178	0.57 0.58	0.43 0.49	214	0.41 0.41	0.59 0.37	217
X_{t-1}=1	0.49 0.44	0.49 0.44	117	0.41 0.54	0.59 0.57	227	0.48 0.42	0.52 0.51	186	0.38 0.59	0.62 0.63	350
Total	131	127	258	171	234	405	211	189	400	222	345	567

	Product M9			Product M10			Product M11			Product M12		
Row Percent Column Percent	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total	X_t=0	X_t=1	Total
X_{t-1}=0	0.63 0.61	0.37 0.50	265	0.53 0.48	0.47 0.30	143	0.52 0.56	0.48 0.43	210	0.48 0.46	0.52 0.36	159
X_{t-1}=1	0.53 0.39	0.47 0.50	203	0.35 0.53	0.65 0.70	241	0.40 0.44	0.60 0.57	219	0.38 0.54	0.62 0.64	235
Total	275	193	468	160	224	384	197	232	429	165	229	394

The frequency counts over stores and months of the event represented by each cell are used to compute probabilities. The top entry in each cell is the row percentage which is the maximum likelihood estimator of the probability of X_{ijt} given X_{ijt-1}. The bottom entry is the column percentage which is the maximum likelihood estimator of the probability of X_{ijt-1} given X_{ijt}. Letting the first coordinate be the value of X at t-1 and the second its value at t then 0.26 in the (0,1) cell of the first contingency table is the probability of a liquor store changing the price of product 1 at t given that he did not change that price in the previous month, while 0.72 is the probability that in the last period a store did not change the price given that the price is changed at t.

The only implications of across-stores staggering are that the (0,1) and (1,0) entries are large relative to the (1,1) entry. In probability terms, the probability of <u>no</u> price change at t-1 conditional on a change at t is larger than the probability of a price change at t-1 conditional on a change at t (column percent); and, the probability of <u>no</u> price change at t conditional on a change at t-1 is larger than the probability of a price change at t conditional on a change at t-1 (row percent).

Liquor stores easily satisfy these implications, a finding consistent with the relativly small number of price changes in consecutive months. Meat stores do not.

We can summarize this information by averaging over products. Aggregating over products instead of over months yields 17 contingency tables. This averaging is appropriate to the extent that there are no systematic differences in the probability of a price change across products which may be the case in our data (see Section 4.A). Since there is a natural ordering to them we graph their entries against the time axis. The top panels in Figure 4 show the proportion of stores that changed prices at t but not at t-1, out of all stores that changed price at t. Let this proportion be denoted by Q_{01}. Q_{01} is the conditional probability of $X_{ijt-1} = 0$ given $X_{ijt} = 1$, which can be computed from each month's contingency table by averaging the column percentage of the (0,1) cell over J products.[17] This probability is to be compared to the average column percentage of the (1,1) cell, Q_{11}.

The other entry of interest in these tables is the (1,0) cell: the number of stores changing price at t-1 but not at t. The average row percentage in this case is denoted by P_{10}; it estimates the conditional probability of $X_{ijt} = 0$ given $X_{ijt-1} = 1$, and is to be compared with the average row percentage of the (1,1) cell, P_{11}. The bottom panels in Figure 4 plot these probabilities against time.

These plots confirm our previous finding that liquor stores are characterized by what we term "regular cyclicity" in the timing of price changes: P_{10} is below P_{11} only in November 1978 and June 1979, while Q_{01} is never below Q_{11}. This pattern of price changes is not that characteristic of the meat-products market. This conclusion is also supported by Tables A5 and A6 in the appendix, which present the ratios P_{10}/P_{11} and Q_{01}/Q_{11} over time for each product separately.

In this section we analyze three features of the data: the proportion of price changes, the number of simultaneous moves and the phenomenon of regular cyclicity. The behavior of liquor stores matches the predictions of a model in which stores are staggered in the timing of each product's price changes. These new findings reinforce the conclusion reached in L&T that prices of wine products are slow to adjust, with the proviso that the timing of the price changes is staggered across liquor stores.

The results for stores selling meat products are mixed. The proportion of price changes are bounded away from zero and one and, on average, stores change prices at the same time as 56 percent

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[17] Q_{01} is defined by

$$Q_{01t} = \frac{1}{J}\sum_{j=1}^{J} \frac{\sum_{i \in N_{jt}} I(X_{ijt}=1, X_{ijt-1}=0)}{\sum_{i \in N_{jt}} I(X_{ijt}=1)} \quad (1)$$

where J is 9 (wines) or 12 (meat products), I(A,B) is the indicator function whose value is 1 when both A and B occur, and zero otherwise, and N_{jt} is the set of stores for which the price of product j is recorded in months t, t-1 and t-2.

of their competitors. Therefore, these stores' behavior exhibits characteristics of across-stores staggering. In many cases, however, the behavior of these stores is not in accordance with the concept of regular cyclicity -- in some instances blatantly so.

The difference in behavior between the two markets, meat products and wines, is certainly interesting, but before we speculate on the reasons for this difference, we should consider the possibility that it is an artifact of the data. For across-stores staggering to be observed we require, in addition to staggering in the timing of price changes across stores, that the duration of a price quotation be greater than one month (the sampling interval). Otherwise, if all prices change within a month, we will not detect across-stores staggering by our definition even though the timing of the price changes may indeed be staggered within the month. Put differently, those stores not exhibiting regular cyclicity defined on a monthly basis may be satisfying a higher frequency regular cyclicity which cannot be observed given the one month length of the sampling interval. Since the average duration of a price within this group of stores is less than two months -- the unweighted mean is 1.72 with a standard deviation of 0.22 (Table 4 in L&T) -- stores selling meat products may fail to show staggering simply because we cannot detect this behavior given our sampling frequency, not because the timing of prices changes are not staggered.

The quantitative implications of this argument can be gauged by analyzing the following benchmark case. Consider a one-product environment with a constant and deterministic rate of inflation and perfect staggering where prices changes once every 45 days and the sampling frequency is 30 days.[18] In this scenario, half the stores will exhibit 2 consecutive price changes. No store will have any consecutive price changes when the duration of a price quotation is 2 months or more. When the average duration is 1.72 we are bound to expect some stores to fail the regular cyclicity test. Given the heterogeneity across products, stores and time present in our data it is, however, a formidable task to

[18] In this example, perfect staggering occurs when each firm changes its price exactly every 45 days and a measure of exactly 1/45 of firms (ignoring integer problems) changes its price every day.

derive the exact benchmark number to which our results ought to be compared with. The upshot of this disclaimer is that the observation of stores failing to exhibit regular cyclicity defined on a monthly basis is not necessarily evidence against the hypothesis of across-stores staggering.

What are the implications of our finding that stores stagger their price changes in a cyclical pattern within each product market? First, this feature clearly undermines the view that sector (product) specific shocks guide the inflationary process (Bruno and Sachs, 1985). In fact, the staggering of price changes over time smooths down sectoral shocks and therefore mitigates, or at least spreads out, their impact on aggregate variables.

Second, the small number of consecutive price changes goes against the notion that price rigidity emerges from a gradual "search and adjust" process, as suggested by some search models (Zeira, 1987; Rob, 1991). This implication, however, is not a surprising one since, in these type of search models, gradual adjustment emerges from <u>real</u> pre-commitment (adjustment costs, irreversibility). Since prices are always set in nominal terms, a high rate of inflation makes the commitment to a real price a reversible decision. When the rate of inflation is 4 percent per month, it seems that the effect of irreversibility on decision making is not that strong.[19]

Across-stores staggering raises questions on the empirical implications of signal extraction models of price-setting behavior. The structure of the shocks that can generate the observed sorting over time of stores should not only discriminate across stores but do so cyclically. This is very unlikely to occur. Nonetheless, one may think of the pattern of regular cyclicity and staggering as emerging from the geographic heterogeneity of monetary shocks. We rebut this view in Section 6.

Across-stores staggering occurs in the market for each individual product, i.e., in the across-

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[19] If our conjecture that inflation erodes commitment is true, our findings are appropriate for high inflation levels only. If the reasons for price rigidity may differ between low and high rates of inflation, inflationary dynamics would differ accordingly. Tommasi (1993b) builds a search model where inflation erodes the informational content of prices. He shows that at some point this effect dominates so that search loses its potential and declines in equilibrium.

stores dimension. In foodstuffs, as in most products, stores (price-setters) sell many different products. The natural question to ask is whether stores, as multiproduct firms, make use of this fact to learn about the inflationary process, or are adjustment costs lumpy enough to prevent such search activity?

This issue is crucial when trying to discriminate among the different models of price-setting behavior. If stores do change different products' prices on different dates one could interpret regular cyclicity as a costly search process where each change in a specific price is an investment in discovering the aggregate shock. If so, signal extraction can still be a dominant factor at the level of the price-setter even though each specific product market exhibits both staggering and regular cyclicity. In addition, when trade is sequential (Lucas and Woodford, 1993; Eden, 1994), store-level price dynamics may closely resemble the dynamics of rigid prices but its implications for the aggregate level are very different. This similarity at the store level, however, breaks down when the store is a multiproduct firm. Extensions of the signal extractions and sequential trading models would suggest the presence of within-store staggering in addition to the observed across-store staggering. By this we mean that when a firm sells many products it should tend to change the prices of some products each date rather than lumping all price changes together.

In order to address this isomorphism between the store-level implications of different models of price-setting behavior, and also because it is interesting in its own right, we analyze the within-store dimension of the data.

4. Within-store synchronization

The issue is whether stores tend to change the prices of different products simultaneously. That is, we ask whether or not the change in the price of a particular product in a particular store is usually accompanied by changes in other products' prices in the same store. If such simultaneity exists we call it within-store synchronization.

Note that we investigate synchronization in the <u>timing</u> of changes in the prices of different products sold in a single store. Other related issues, such as the cross-correlation in the size of the price changes, are not explored. Synchronization in the timing of price changes may have very different implications from those of correlation in the size of change. We comment briefly on this issue in Section 6.

A. Proportion of Price Changes

A natural measure of the degree of within-store synchronization is the proportion of products whose prices changed during a month. In our notation, this proportion is

$$\varphi_{it} = \frac{1}{|G_{it}|} \sum_{j \in G_{it}} X_{ijt} \qquad (2)$$

where G_{it} is the set of products whose prices were recorded in store i during months t-1 and t (i.e., the number of products sold at t-1 and t, or the number of non-missing values of X_{ijt}) and $|G_{it}|$ is the cardinality of the set. We actually define φ_{it} for the subsample of stores that sell at least three products in each class, $|G_{it}| \geq 3$. Recall that the stores in our sample sell either meat products or wines, but not both. Hence, synchronization between classes of products cannot be addressed with these data.[20]

We start by asking what values of φ_{it} should be expected when there is within-store synchronization. Clearly, we cannot provide a definite answer to this question without a structural model,

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[20] A problem with φ is that we do not know whether more than one change in price occurred within the month, so that an observed φ of 1 can be the result of different values for φ's defined on, say, a weekly basis. Our definition of synchronization allows for this possibility so that two products are said to be synchronized if one changes its price the first day of the month and the other does so the last day of the same month. Another issue is that we sample a small fraction of the products sold by the store so that the true φ may be very different from the observed φ. Our results are, of course, conditional on the sample. To the extent that the sample of products within each class is random we could carry over the conclusions of the analysis to the entire population in each class of products.

but we can be fairly confident that when inflation is as high as it was during the period – 3.9 percent per month – the probability of a store not changing <u>any</u> of its products' prices during a month is very low when the decision to change price is independent across products. Hence, observing many φ_k's equal to zero should be indicative of within-store-synchronization.[21,22] Table 4 presents the frequency distribution of φ_k for wines and meat products.

Table 4: The distribution of φ_k

		0	0.0-0.2	0.2-0.4	0.4-0.6	0.6-0.8	0.8-1	1	Total
WINE	Obs	236	27	51	18	18	12	46	408
	%	57.8	6.6	12.5	4.4	4.4	2.9	11.3	100.0
MEAT	Obs	139	28	152	169	243	66	111	908
	%	15.3	3.1	16.7	18.6	26.8	7.3	12.2	100.0

The difference between wine and meat products is quite striking. While most of the observations in wines correspond to $\varphi = 0$, the distribution of φ for meat products is much more balanced. If $\varphi_k = 0$ is the only positive evidence for synchronization in the timing of price changes

[21]It is important to recall that there was no slowdown in the rate of inflation during this period.

[22] The same conclusion could be reached if all prices were changed during the month, $\varphi_k = 1$. A problem with this conclusion is that, given a positive rate of inflation, and with a long enough interval of time between samplings, a store will eventually change all its prices and we will observe $\varphi_k = 1$. To deduce that there is synchronization across products is, of course, misleading. In this case, $\varphi_k = 1$ is evidence of nothing but the fact that the frequency of sampling is too low relative to the rate of inflation. Hence we should be cautious in the interpretation of φ's equal to one. We do not, however, believe this is an issue in our data. Recall that in this period, when the average monthly rate of inflation was 3.9 percent, the average duration of a price quotation was 2.2 months. Had we used quarterly data, our definition of synchronization would guarantee that we find perfect within-store synchronization in the data. But since we use monthly data, the severeness of this problem is reduced. In particular, note that for wine products the average duration of a price quotation is 4 months.

across products we must conclude that most wine stores synchronize the timing of the price changes of their products, while stores selling meat products do so to a lesser extent.[23]

In the remainder of this section we present additional evidence favoring the within-store synchronization hypothesis. We provide formal tests of the hypothesis, but doing so requires a series of compromising assumptions. It is therefore comforting to note that the direct evidence and conclusions from Table 4 hold up to more formal analysis.

The expected value of φ_{it} is

$$E(\varphi_{it}) = \frac{1}{|G_{it}|}\sum_{j\in G_{it}} P_{ijt} \tag{3}$$

where $P_{ijt} = \text{Prob}\{X_{ijt} = 1\}$ is the unconditional probability of observing a price change in product j at store i during month t.

The null hypothesis to be tested is the case of no within-store synchronization. This is interpreted as stating that the sequence $\{X_{ijt}\}$ is pairwise independent over products j. Under this hypothesis, the variance of φ_{it} is

$$V(\varphi_{it}) = \frac{1}{|G_{it}|^2}\sum_{j\in G_{it}} P_{ijt}(1-P_{ijt}) \tag{4}$$

and for large G,

$$\frac{\varphi_{it} - E(\varphi_{it})}{V(\varphi_{it})^{1/2}}$$

[23] In an attempt to see whether the heterogeneity in the number of products sold by the store, $|G_{it}|$, has an effect on the conclusions because of a possible effect of $|G|$ on φ, we divided the observations into those corresponding to stores having $3 \le |G_{it}| \le 5$ and those with $G_{it} \ge 6$. The conclusions were similar to those of Table 4.

is approximately distributed as a standard normal variable. If $\{X_{ijt}\}$ is a sequence of independent random variables over stores i, then

$$T_t = \sum_{i \in N_t} \frac{[\varphi_{it} - E(\varphi_{it})]^2}{V(\varphi_{it})} \sim \chi^2_{|N_t|} \tag{5}$$

where N_t is the set of stores with non-missing φ at time t.

We focus on T_t since $|G|$ is relatively smaller than N in our data. T_t is not a statistic since it depends on unknown parameters. Note that neither $E(\varphi)$ nor $V(\varphi)$ are observed nor does the null hypothesis specify their value. $E(\varphi)$ and $V(\varphi)$ have to be estimated and for this we need estimators of the probabilities of a price change in all the products. Under the null hypothesis we do not need to estimate the joint probability of $X_{i1t},\ldots,X_{iJt}$ and then integrate out the marginal probabilities. Thus, under the null hypothesis, estimation of P_{ijt} is greatly simplified since it allows us to ignore the information embodied in the behavior of the other products. Since P_{ijt} cannot be estimated for every store-product-month observation we have to make some assumptions. The first one is

$\{X_{ijt}\}$ is iid over i. (A1)

This assumption restricts the probability of a price change to be the same across stores, but allows for heterogeneity in the size of the price change. For all stores i, $P_{ijt} = P_{jt}$. Note that $E(\varphi_{it})$ and $V(\varphi_{it})$ may vary across stores because of differences in the number and composition of products sold at time t.

We now consider two distinct scenarios for estimating P_{jt}. The first scenario assumes

$\{X_{ijt}\}$ is independent, not identically distributed, over t. (A2)

Assuming A1 and A2, a consistent estimator of P_{jt} under the null hypothesis is the sample mean of X_{ijt} over stores i

$$\bar{X}_{jt} = \frac{1}{|N_{jt}|} \sum_{i \in N_{jt}} X_{ijt} \qquad (6)$$

where N_{jt} is the set of stores selling product j in months t and t-1.

This estimator of the unconditional probability of a price change was analyzed in Section 3.A and plotted in Figure 3 for every product. X_{jt} is the proportion of stores changing product j's price at t. When substituting the P_{ijt}'s by the sample means of the X_{ijt}'s the test has the nice feature that it compares a measure in the within-store dimension with a measure in the across-store dimension. We will return to this interpretation after presenting the results of the test.

The second scenario for estimating P_{jt} takes explicit account of the dynamics in the X_{ijt} process. Assume

$$P(X_{ijt} / I_{it}) = P(X_{ijt} / X_{ijt-1}). \qquad \text{(A2')}$$

This assumption states that the probability of observing X_{ijt} conditional on all the relevant information available to store i at time t, I_{it}, is the same as that probability conditional only on information on what happened to product j during the previous period. This assumption embeds the restriction imposed by the null hypothesis jointly with a Markovian assumption. Note, too, that the conditional probability is time invariant, which may be a strong restriction even though the macroeconomic environment -- the inflation rate -- was quite stable during the period. In a sense (A2') is the complement of (A2). It assumes a particular type of time dependence for the $\{X_{ijt}\}$ process, but restricts it to be stationary over time, whereas (A2) allows for non-stationarity but assumes independence over time.

Under assumptions A1 and A2' we can dispense with the store and time subscripts and denote the probability of a price change in product j conditional on X_{ijt-1} as $P_j(0)$ and $P_j(1)$, according to whether X_{ijt-1} is 0 or 1. The stochastic process $\{X_{ijt}\}$ is a time-invariant Markov chain over t. There are different chains for different products, but all stores follow identical processes. The one-step transition probabilities matrix is

$$\wp_j = \begin{bmatrix} 1-P_j(0) & P_j(0) \\ 1-P_j(1) & P_j(1) \end{bmatrix} \quad . \tag{7}$$

Under assumptions A1 and A2' the maximum likelihood estimators of the one-step transition probabilities are the row percentages in Table 3. In order to get the unconditional probabilities appearing in (3) we need to know the probability distribution of the initial state X_{ij0}. Given the initial distribution we can obtain the unconditional probability of a price change at any time t in product j

$$P_{jt} = (1-P_j^{(0)})P_j(0)^{(t)} + P_j^{(0)}P_j(1)^{(t)} \tag{8}$$

where, say, $P_j^{(0)}$ is the probability of a price change at t=0 and $P_j(0)^{(t)}$ is the probability of a price change at time t conditional on no price change at t = 0. More precisely $P_j(0)^{(t)}$ is the (0,1) element in the t-step transition probabilities matrix $\wp_j^{(t)}$ ($\wp_j$ multiplied by itself t times).

It turns out that the limiting probabilities π_j and $1-\pi_j$ of the Markov chains given by the matrices in Table 3 are arrived at very rapidly. Irrespective of the values of the initial probabilities, it takes at most 2 or 3 periods to get within three decimal places of the limiting probabilities. That is, P_{jt} is very close to π_j for $t \geq 3$. We therefore use estimates of π_j to estimate P_{ijt} in (3). These are given by

$$\hat{\pi}_j = \frac{\hat{P}_j(0)}{1+\hat{P}_j(0)-\hat{P}_j(1)} \qquad (9)$$

where the $\hat{P}$ are read off directly from Table 3. Table 5 summarizes the features of the different estimates of P_{jt}. The entries are statistics corresponding to the distribution of the product-specific estimates ($X_{j.}$ is the average of X_{jt} over t).

Table 5: Unconditional probabilities of a price change

	MEAN	STD DEV	MIN	MAX
WINES $\hat{\pi}_j$	0.23	0.02	.20	.28
WINES $X_{j.}$	0.24	0.03	0.21	0.31
MEATS $\hat{\pi}_j$	0.53	0.07	.38	.61
MEATS $X_{j.}$	0.53	0.07	0.40	0.62

There does not seem to be much difference between the two ways of estimating P_{jt}. In addition, the small standard deviations of the estimates indicate that there is not much variation in P_{jt} across products. This feature is important since it implies that φ_{it} is close to a binomial random variable under the null hypothesis.

It should be noted that the absence of within-store synchronization does not rule out the possibility that a large proportion of products behave in the same way. This is, in fact, expected due to the high level of inflation during the period. Lack of synchronization merely says that the joint probability of $X_{i1t},\ldots,X_{iJt}$ is the product of the marginal probabilities for each product: it can be anything between 0 and 1.

The test in (5) was conducted 17 times, for each month from February 1978 till June 1979, using X_{jt} and $\hat{\pi}_j$ in place of P_{ijt}. Table 6 presents the number of rejections at a 5 and 10 percent significance level.

Table 6: Chi-square tests of within-store synchronization

Number of rejections in 17 tests

	WINE	PRODUCTS	MEAT	PRODUCTS
	X_{jt}	$\hat{\pi}_j$	X_{jt}	$\hat{\pi}_j$
Rejections				
5%	11	13	16	16
10%	13	16	17	17

As mentioned above, the version of the test using X_{jt} as the estimator of P_{jt} has a simple interpretation: it compares a measure of within-store synchronization (φ_{it}) with an average measure of across-stores synchronization. The latter is based on X_{jt}, the proportion of stores changing the price of product j during a month, which was, in fact, used to characterize across-stores staggering in Section 3.A.

If within-store synchronization is the result of a matching between the products sold by the store and an inflationary shock then both φ_{it} and X_{jt} should follow similar patterns. In addition, heterogeneity in the inflation process, across products or over time, should not cause much of a difference between φ_{it} and X_{jt}. Put differently, the results of the test mean that the observed within-store synchronization is unrelated to the actual path of inflation. Since within-store synchronization does not mirror the inflationary process the reasons for its existence lie somewhere else.

The above arguments can be depicted graphically once we restrict the process $\{X_{jit}\}$ to be iid over stores, products and time. Then φ_{it} and X_{jt} are identically distributed for any i, j and t. Figure 5 shows the histograms of φ_{it} and X_{jt} in the sample. Note that for both wines and meat products, the distribution of φ has thicker tails than the distribution of X. In particular, the mass at 0 and at 1, is significantly higher for φ than for X. As mentioned above, if the observed pattern of φ merely reflected the inflationary process, the same should be true of X. Figure 5 strongly rejects this possibility.

If the unconditional probability of a price change is the same across products, then, under the null hypothesis, the number of price changes in each store at any month should be distributed as a binomial random variable with parameters G_{it} and the common probability P_{wt} or P_{mt} for wines and meat products, respectively.[24] Table 5 indicates that this assumption may be appropriate for our data and, in fact, we can estimate P_{wt} and P_{mt} either by X_{jt} averaged over products or by the average of $\hat{\pi}_j$ over products.

As mentioned at the beginning of this section, the most compelling evidence in favor of within-store synchronization in the timing of price changes is given by the frequent occurrence of the events $\varphi_{it} = 0$ and $\varphi_{it} = 1$. We are now in a position to compare the observed frequencies of these events (Table 4) with the expected frequency under the binomial assumption.

For each value of $|G_{it}| \geq 3$ and for every month we compute the binomial probabilities of observing zero and $|G_{it}|$ price changes using the estimated P_{wt} and P_{mt}. These probabilities are multiplied by the number of stores selling $|G_{it}|$ products to obtain the expected frequency of zero or

[24] This holds for any finite value of the sample size G_{it}.

$|G_t|$ price changes in each month. Within-store synchronization predicts that the observed frequencies will be higher than the expected ones. Table 7 corroborates this prediction.

Table 7: Observed and expected frequencies of extreme events

		Zero Changes	All Changes
WINES	Observed	236	46
	Exp. X_{jt}	150.5	10.7
	Exp. π_j	100.8	1.2
MEAT Prds.	Observed	139	111
	Exp. X_{jt}	41.6	69.4
	Exp. π_j	39.8	58.8

B. Pairwise correlation in the timing of price changes

So far our approach to the measurement of within-store synchronization captures behavior within a period. Another – perhaps more dynamic – approach is the co-evolution of two different products j and k, X_{ijt} and X_{ikt}, within each store over time. An additional implication of pairwise independence in the timing of price changes is that the covariance over time between any two pairs of products sold in the same store is zero. This issue is analyzed in this subsection, thereby putting together, in some sense, the concept of regular cyclicity with the static notion of within-store synchronization.

We focus our analysis on the behavior of the cross-product $X_{ijt}X_{ikt}$. We define the indicator function $S_t(j,k)$ as follows: when both products behave similarly $S_t(j,k) = 1$; else $S_t(j,k) = 0$. That is, when either both $X_{ijt} = X_{ikt} = 1$ or $X_{ijt} = X_{ikt} = 0$, $S_t(j,k) = 1$. The mean value of $S_t(j,k)$ over time, $S_L(j,k)$, is the proportion of synchronization or matching between two products j and k in store i.

Over all stores and pairs of distinct products we obtained 579 and 1069 $S_L(j,k)$'s for wines and meat products, respectively. Table 8 displays features of the distribution of $S_L(j,k)$. Recall that within-store synchronization implies "high" values of S_L.

Table 8 : Cumulative distribution of $S_L(j,k)$

	N	MEAN	MIN	5%	10%	25%	50%	MAX
WINES	579	0.867	0.333	0.588	0.667	0.800	0.889	1.000
MEATS	1069	0.581	0.000	0.273	0.364	0.471	0.588	1.000

A rough benchmark figure for the expected proportion of matchings, $S_L(j,k)$, under the assumption of no within-store synchronization can be obtained from Table 5. For wines we are led to expect an $S_L(j,k)$ around 0.0576 (= 0.24^2) and no larger than 0.0961 (= 0.31^2), while for meat products $S_L(j,k)$ should hover around 0.281 (= 0.53^2) and no more than 0.384 (0.62^2). It is clear that the observed proportions of matchings are larger than the expected ones. [25]

Clearly, meat products and wines do not behave in the same way. Recall that we are analyzing the same time period in each product so that the stores selling these products operate in the same macroeconomic environment. It may be that aggregate variables, such as those related to monetary expansion, or even the average rate of inflation, transmit into meat products with much more noise. In other words, meat products are subject to more idiosyncratic shocks. This may be

[25] This, of course, does not constitute a formal testing procedure. Within-store synchronization means that the joint probability of observing a price change in products j and k equals the product of the marginal probabilities of a price change in goods j and k. This means that the covariance over time between X_{ijt} and X_{ikt} is zero. Testing for zero covariances is not pursued here because (a) it is difficult to assign a reliable standard error to the estimator of the covariance since it depends on the serial correlation pattern of each $\{X_{ijt}\}$ sequence, and (b) a formal procedure would be based on large sample theory whose finite-sample properties are unknown. This is a problem since each $S_L(j,k)$ is an average of at most 17 observations and usually much less than that.

responsible, at least in part, for the fact that synchronization within the store is not as complete in stores selling meat product as it is in liquor stores.

5. Negative and positive price changes

This section examines the co-existence of positive and negative nominal price changes within the store. The phenomenon of negative nominal changes during a period of high inflation is interesting. With an inflation rate of about 3.9 percent a month, one is tempted to think that very few nominal prices, if any, are likely to adjust downward. Our data show that this is not so. About 12 percent of all changes in our sample are downward changes in this period (11.1 percent in meat products and 14.7 percent in wines).

In the literature on equilibrium distributions of real prices the assumption of relative two-sided (idiosyncratic) shocks is usually invoked to generate a stable distribution of the relative prices. It is therefore comforting to know that even when aggregate shocks generate a fairly high rate of inflation, there seems to be evidence pointing towards the presence of idiosyncratic shocks in the opposite direction.[26] Note, however, that a downward adjustment of nominal prices cannot, by itself, imply the existence of idiosyncratic shocks. It is the co-existence of price reductions of individual products and a positive and stable inflationary process that suggests the presence of strong idiosyncratic shocks in addition to the aggregate shock.[27,28]

[26] Tsiddon (1993) and Caballero and Engel (1991) present models based on two-sided shocks.

[27] Recall that the standard deviation of the monthly rate of inflation is 1.9 percent. To see whether negative shocks come from a distribution of idiosyncratic shocks or from aggregate shocks we ran a series of regressions of the number of negative nominal price changes across all stores on the unexpected component of inflation (both in linear and in linear-quadratic forms). We could not detect a single equation that shows a negative coefficient. Negative price changes are not related to negative surprises in the rate of inflation. We therefore conclude that the source for these changes is idiosyncratic.

[28] An alternative interpretation may be the occurrence of "sales" not related to shocks of any type. Casual examination leads us to believe that "sales" are not a common phenomenon in grocery stores in Israel. They are more prevalent in supermarkets which, however, are not included in our data.

We have argued before that within-store synchronization can result from the existence of store-specific costs of adjusting prices. However, there may be other explanations for this observation. One competing hypothesis is that monetary shocks are distributed unevenly across geographical regions.[29] As we shall see, the timing of the negative nominal price changes offers a viable way of contrasting the two hypotheses.

Suppose there exist idiosyncratic shocks that are independently distributed across products as well as across stores. Suppose that a store "observes" a negative shock in the market for product j. If there were no store-specific component to the costs of adjusting prices, then the store would adjust the price of product j downward only at the moment the product-specific negative shock arrives. This implies that the timing of negative price changes is <u>uncorrelated</u> with the timing of positive price changes.

If a negative shock to a particular product in a specific store coincides with a positive regional monetary shock affecting the store -- the unevenly distributed shock -- then there are weaker incentives to accommodate the negative idiosyncratic shock since it is partly or fully compensated for by the positive regional shock. In this case, the timing of negative and positive changes in prices within a store ought to be <u>negatively correlated</u>.

All the above implications hold under the assumption of no store-specific adjustment costs. If there are store-specific costs to changing prices, the store should try to bunch together negative and positive changes in prices, implying a <u>positive</u> correlation between the timing of positive and negative price changes.

Figure 6 presents the degree to which the timing of positive and negative price changes coincide. The horizontal axis shows the proportion of negative price changes that occur simultaneously (in the same month) with positive price changes within the same store. The vertical

[29] Note, however, that the data were collected in Israel, whose area is just under 22,000 square km.

axis indicates the frequency counts. In 40 stores all negative price changes coincided with positive price changes. In 11 stores there were negative price changes only when there were no positive ones.[30] We interpret the left-skewness of Figure 6 as favoring the menu-cost explanation of the existence of within-store synchronization over the explanation of a geographically uneven macro shock.

6. Interpretation of the evidence

Our analysis of the data indicates that the timing of price changes is synchronized within each store but that stores are staggered over time in quoting new prices. We believe that these findings lend greater support to some theories of price dynamics than to others. In this section we comment on how different theories fit these results.

A. Menu costs models

The menu cost paradigm is consistent with our findings when these adjustment costs satisfy the following requirements: (i) they are significant to the seller, in the sense that they are not to be incurred continuously, and (ii) some component of these costs is store-specific. The adjustment costs are, therefore, not exclusively a result of the characteristics of each product but also of the characteristics of the price-setter. This last requirement will induce a store to synchronize its price changes. The term "menu cost" comes alive: the cost of printing a new menu is shared by all products. If such store-specific costs are indeed important, then single-product menu cost models may give a very distorted picture of price dynamics.

Note, however, that store-specific costs should induce synchronization only in the timing of price changes, but should not carry implications as to the size of the price changes for individual

[30] Of these, 7 are liquor stores and 4 are stores selling meat products.

products. This justifies our focus on the synchronization in the timing of such changes.

B. Informational externalities

Another explanation that fits the within-store synchronization of price changes is based on informational externalities. Ball and Cecchetti (1988) discuss a mechanism in which each price-setter derives information on inflationary pressures from observing the decisions made by other price-setters when they change prices. They show that such an externality can generate an equilibrium with staggered price-setting.

This explanation does not contradict the menu cost hypothesis. In conjunction with the menu cost explanation, it amplifies the within-store-synchronization phenomenon, and yields an intuitive and plausible mechanism that explains staggering across stores.

C. Signal extraction models

Lucas's (1973) explanation that stores change most of their prices in response to a macroeconomic shock, e.g., an unexpected monetary expansion, does not fit the data well. If the shock is perceived by all agents at the same time (i.e., if there is no asymmetric information) all stores will respond in a synchronized fashion, leading to across-store synchronization. The lack of synchronization observed in Figures 1 does not support this implication. It would be very difficult to suggest a convincing argument whereby macro shocks lead to within-store synchronization but not to across-store synchronization. Hence, within-store synchronization cannot be the result of macro shocks.

One way of reconciling this model with the findings is that the effects of macro shock are unevenly distributed geographically, say, with different factor loadings in different locations. Moving away from a pure macro shock can potentially generate the across-store staggering and within-store synchronization observed in the data. This explanation was considered in Section 5, where we documented the coexistence of positive and negative price changes within the same store. The data seem to reject the geographic hypothesis as well.

We do not interpret the data as suggesting that the effects of partial information on price dynamics are minimal. The data only suggest that at high rates of inflation the economic implications of incomplete information are overshadowed by the economic implications of the existence of friction in setting new prices. Thus, this is simply another costly aspect of inflation: at high rates of inflation price-setters must pay more attention to frictions than to gathering and processing information. Inflation therefore makes price-setting a more mechanical process. We will return to this issue later.

D. Sticker price model

Diamond (1993) proposes yet another mechanism to justify the sluggishness of the aggregate price level: identical products may have different prices since prices are set at the time of delivery to the store and remain unchanged unless a crucial change in the environment occurs. Our data do not support this hypothesis; for it to be consistent with our findings one needs to assume that all products are delivered simultaneously to each store so as to generate within-store synchronization, and that there is a non-degenerate distribution of delivery dates across stores. This distribution should be widely spread-out in order to generate the observed across-stores staggering in the timing of price changes, which was defined on a monthly basis. These are strong assumptions, that are unlikely to hold for the type of products analyzed here.

E. Search theory

In L&T we showed that the price dispersion in each (homogeneous) product market is very large. Consequently, consumers have incentives to search for the lowest price. There is, in fact, a rich literature connecting search theory to inflation but most of its implications cannot be addressed with our data.

Search, however, is not confined to consumers only. In an inflationary and uncertain environment, sellers also are not fully aware of nominal price changes and, therefore, every new price quotation brings new information on market conditions to consumers and sellers alike.

To the best of our knowledge no model exists, as yet, in which consumers and sellers search in the context of multiproduct firms. Hence, we can only conjecture about the constraints such a model would impose on the data. In broad terms and mainly from an information-gathering perspective, staggering price changes within the firm amounts to following a sequential search procedure; synchronization of price changes is analogous to a fixed sample search approach. It is well known that, under fairly general conditions, sequential search is a better strategy. In our dataset, nevertheless, we find that stores synchronize the timing of their products' price changes, i.e., they choose the fixed sample approach.

Two possible explanations of this paradox can be advanced. First, the environment may be very volatile and little, or nothing, can be inferred from observations of one product on the others. Second, the existence of frictions at the store-level make the staggering of price changes a very costly alternative. Both explanations are not mutually exclusive; both may render a sequential search strategy non-optimal.

Moreover, since relative price volatility is partly attributed to frictions in price setting (L&T), these frictions seem to have a very close connection to the fact that there is no sequential search. This, however, is merely another manifestation of what was noted earlier: as inflation increases, frictions become more important, and behavior becomes more mechanical.

To sum up, we believe the empirical findings of within-store synchronization and of across-stores staggering are important because, first, they validate the assumption made in much of the "sticky prices" literature that decisions are staggered across price-setters, and not across products. Second, they provide further empirical support for the conjecture that price rigidity is due to mechanical reasons, i.e., to menu costs, and not to informational asymmetries. And last, they indicate that further research on the dynamics of prices should take into account the multiproduct character of the price-setter.

7. The store-specific menu costs hypothesis

Accepting the view that within-store synchronization in the timing of price changes emerges, at least in part, as a result of the existence of a store-specific component in the cost of adjusting a price quotation raises some interesting issues. Although menu cost models for a multiproduct price-setter have received little attention from the theoretical perspective,[31] we heuristically derive some simple restrictions on the data by extending the logic of the single product model.

It is commonly believed that the existence of small price changes constitutes evidence against the menu cost proposition. It follows that if many small changes are observed, the menu cost paradigm has very little (if anything) to say about actual price dynamics. This deduction, however, is not applicable in a multiproduct setting.

If the fixed costs associated with the price-setter, relative to those associated with the product, are the dominant component, then the well-known (S,s) policy in its narrow definition is no longer optimal. While prices still change discontinuously, one should expect fairly little regularity in the size of the price change of each product.[32]

To illustrate this point, consider the case in which the only adjustment costs are those attached

[31] See Sulem (1986) and Sheshinski and Weiss (1992).

[32] This contradicts the conclusion of the single product case. In that case, the (S,s) boundaries are fixed as long as the characteristics of inflation are fixed. Thus with a (stochastically) stable inflation one expects a constant proportional change in price.

to the price-setter. If a decision is made to change prices, then the prices of all products are changed, i.e., perfect within-store synchronization is the rule. As long as idiosyncratic shocks are significant relative to aggregate inflation, when a price-setter decides to change (all) prices the magnitude of the change in each product's price can be anything: some prices may change more than others or may change in opposite directions. The only common fact is that in all these changes, each price is set to its optimal level. In addition, if store-specific costs are large, an appropriate weighted-average of price changes within a store should also be "large".[33] In the more general case, when the costs of adjustment include a component associated with each product, some prices may not change at all or may change on different dates, implying less than perfect within-store synchronization, but the rule that conditional on a change, the average change should be large, still holds.

Having no information on sales or on the cross-derivatives of the profit function, we use the arithmetic average of price changes as a proxy for the correct weighted-average of price changes. Note that we restrict ourselves to positive price changes. Let DP_{ijt} be the percentage change in the price of product j in store i during month t and select those observations for which DPijt > 0. The average change within store i is given by DP_{it},

$$DP_{it} = \frac{1}{|G_{it}|}\sum_{j \in G_{it}} DP_{ijt} \qquad (10)$$

where G_{it} is the set of products whose prices changed during month t in store i and $G_{it} \geq 3$. Table 9 characterizes the distribution of DP_{it} over stores.

[33] The appropriate weight is the weight that accounts not only for the sales of the product but also for the effect of the change in the product's price on total revenues (Sheshinski and Weiss, 1992).

Table 9 : Cumulative distribution of DP_k

	N	MEAN	MIN	5%	10%	25%	50%	MAX
WINES	148	0.139	0.007	0.015	0.027	0.059	0.104	0.558
MEATS	744	0.090	0.006	0.031	0.041	0.058	0.081	1.016

Since the average monthly inflation rate was 3.9 percent, we could use this number to define a "small" price change. In wines, 15.5 percent of the average price changes are small while in meat products the corresponding figure is 9.1 percent.[34] A comparison of each DP_k to the corresponding monthly rate of aggregate inflation (CPI) indicates that 11 percent of the changes in liquor stores are less than the inflation rate, while for stores selling meat products this figure is 14 percent. In sum, only between 10 and 15 of all average price changes are "small" according to the definition employed.

While small price changes in specific products are not evidence against menu cost models in the multiproduct firm setting, the fact that small average changes within each store are infrequent reconfirms our previous conclusion that the phenomenon of within-store synchronization is, at least in part, due to significant store-specific menu costs.

Theory provides other restrictions that should be satisfied by the data if within-store synchronization is related to store-specific menu costs. The main implication is that DP_k should be positively affected by expected inflation and not related to unexpected inflation. In fact, the mean of DP_k over all stores and months increases from 9.8 percent in 1978-1979:6 to 11.9 percent in 1981-1982. At the same time, the average monthly inflation rate mounted from 3.9 percent to 7 percent.

The relationship between DP and unexpected inflation was examined via a regression of DP_k

[34] In liquor stores, 23 price changes were less than 3.9 percent. 39 percent of them occur in 3 months (May 1978, and February and March 1979). In stores selling meat products, 68 price changes were below 3.9 percent; 37 percent of them also occur in 3 months (March and December 1978, and in March 1979).

on unexpected inflation and its square. In all the regressions, for meat products and wines separately, with and without store dummies, the coefficient of the unexpected part of inflation is statistically not significant.[35]

8. Conclusion

A price-setter usually sets prices for many different products. This obvious fact is an aspect of price-setting behavior which has been neglected in most of the theoretical and empirical work on the subject. The purpose of this paper is to draw attention to this issue. We do this by empirically investigating a rich body of data on prices of meat products and wines collected at the store level in Israel.

The data show that when stores -- price-setters -- change prices, they change the prices of most of the products they sell. That is, there exists within-store synchronization in the timing of price changes. In addition, stores are staggered in the timing of their price changes. These findings justify the use of staggered price-setting mechanisms in the debate over the role of monetary policy.

We also contrast the implications of some of the prominent models of price-setting behavior with the data. Among the potential explanations, the one suggested by the menu cost model seems to be the one most consistent with the data. While we do not formally test the menu cost model against the other alternatives models we tend to conclude that, at least for foodstuffs, the menu cost approach describes the data well. The results from L&T reinforce this conclusion.

[35] The series on unexpected inflation is the one used in L&T. To conserve space we do not report the results of these regressions, which are analogous to those appearing in L&T.

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APPENDIX

TABLE A1: SIMULTANEOUS PRICE CHANGES: WINES

Store	$K_{i..}$	Share of Competitors	Number of Products
1	7.27	0.45	7
2	5.38	0.29	3
3	5.64	0.36	8
4	5.00	0.34	1
5	6.16	0.36	5
6	4.00	0.44	1
7	5.76	0.35	9
8	2.83	0.20	5
9	5.37	0.28	2
10	5.31	0.30	5
11	9.00	0.53	3
12	8.77	0.57	8
13	12.00	0.48	1
14	3.50	0.22	8
15	7.90	0.46	7
16	5.25	0.30	4
17	8.00	0.42	2
18	9.08	0.61	6
19	7.00	0.32	1
20	9.09	0.57	9
21	7.57	0.39	3
22	4.85	0.35	4
23	5.08	0.34	8
24	7.88	0.51	6
25	13.00	0.87	1
26	9.13	0.52	6
27	4.33	0.23	3
28	6.33	0.43	2
29	8.67	0.58	1
30	3.60	0.23	1
31	8.21	0.54	8
32	8.28	0.52	8
33	8.02	0.55	9
34	5.00	0.29	1
35	6.00	0.33	4
36	8.15	0.51	7
37	6.30	0.41	8
38	5.46	0.36	9
39	3.80	0.24	7
40	14.00	0.61	1

Notes:

$K_{i..}$ is the number of stores changing price of product j in month t simultaneously with store i, K_{jt}, averaged over the number of products j sold by store i and over the number of months in which these products where sold.
The share of competitors equals K_{jt} divided by the number of stores selling product j during month t minus 1, averaged over products and months.

TABLE A2: SIMULTANEOUS PRICE CHANGES: MEAT PRODUCTS

Store	$M_{..}$	Share of Competitors	Number of Products	Store	$M_{..}$	Share of Competitors	Number of Products
1	17.96	0.60	6	46	17.98	0.58	4
2	8.56	0.57	3	47	8.22	0.49	2
3	8.95	0.57	3	48	15.22	0.57	1
4	8.00	0.52	1	49	17.93	0.59	9
5	16.71	0.49	4	50	7.00	0.37	1
6	18.79	0.61	6	51	17.79	0.55	8
7	13.97	0.39	5	52	15.17	0.56	1
8	15.00	0.67	1	53	14.25	0.66	1
9	18.28	0.61	7	54	18.11	0.60	6
10	20.18	0.59	6	55	17.66	0.56	8
11	7.71	0.51	3	56	18.92	0.59	6
12	18.05	0.55	4	57	8.25	0.52	3
13	8.08	0.55	3	58	23.40	0.68	5
14	18.61	0.58	7	59	7.61	0.53	2
15	8.56	0.54	3	60	16.00	0.38	1
16	17.48	0.58	9	61	18.22	0.58	3
17	6.80	0.38	2	62	19.12	0.62	9
18	9.35	0.58	2	63	18.60	0.61	5
19	16.23	0.52	9	64	18.40	0.60	3
20	17.27	0.51	4	65	15.75	0.53	8
21	16.98	0.48	2	66	18.84	0.57	7
22	7.46	0.67	1	67	18.82	0.58	7
23	8.15	0.58	2	68	18.76	0.63	9
24	8.13	0.55	1	69	16.66	0.59	4
25	8.48	0.53	3	70	7.87	0.49	3
26	14.96	0.54	2	71	7.33	0.45	1
27	17.90	0.58	3	72	18.09	0.60	8
28	16.65	0.51	2	73	9.33	0.56	1
29	19.00	0.43	1	74	19.11	0.60	7
30	18.28	0.57	2	75	20.45	0.64	7
31	22.57	0.54	2	76	20.01	0.61	4
32	17.61	0.54	2	77	18.15	0.58	8
33	18.10	0.58	8	78	16.52	0.46	4
34	17.98	0.55	8	79	18.18	0.55	5
35	18.71	0.57	7	80	7.67	0.43	1
36	9.43	0.63	3	81	18.03	0.59	9
37	8.75	0.57	3	82	19.00	0.71	2
38	22.75	0.58	3	83	17.81	0.55	2
39	19.40	0.59	6	84	17.30	0.57	8
40	8.05	0.48	2	85	20.13	0.58	4
41	17.33	0.57	8	86	19.29	0.58	4
42	19.98	0.58	3	87	19.24	0.64	3
43	15.05	0.57	1	88	10.13	0.63	3
44	9.02	0.56	3	89	16.50	0.61	1
45	16.87	0.56	9	90	12.38	0.51	1

Notes: See notes to Table A1.

TABLE A3: CONSECUTIVE PRICE CHANGES: WINES

STORE	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
1	0.29	0.11	0	0	0	0	.	.	.	.	.	.	.	.	.	.
2	0.57	0	0	0	0	0	0	0	0	0	.	.	.	.	.	.
3	0.06	0.09	0.04	0	0	0	0	0	0	0	0	0	0	0	0	0
4	0.25	0	0	0	0	0	0	0	0	0	.	.	.	.	.	.
5	0.18	0.05	0	0	0	0	0	0	0	0	0	0	0	0	0	0
6	0	0	0	0	.	.	.	.	.	.	.	.	.	.	.	.
7	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
8	0.09	0.08	0	0	0	0	0	0	.	.	.	.	.	.	.	.
9	0.33	0	0	0	0	0	0	0	.	.	.	.	.	.	.	.
10	0.14	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0	0	0	0	.	.	.	.	.	.	.	.	.	.	.	.
12	0.06	0	0	0	0	0	0	0	0	.	.	.	.	.	.	.
13	0	0	0	0	.	.	.	.	.	.	.	.	.	.	.	.
14	0.05	0.07	0	0	0	0	0	0	0	0	.	.	.	.	.	.
15	0.13	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0	0
16	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	.	.	.	.	.	.	.	.
18	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0	0	0	0	0	0	0	0	.	.	.	.	.	.	.	.
20	0.04	0.03	0	0.05	0	0	0	0	0	0	0	0	0	0	0	0
21	0	0.20	0	0	0	0	0	.	.	.	.	.	.	.	.	.
22	0.07	0.10	0	0	0	0	0	0	0	0	.	.	.	.	.	.
23	0.06	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	.
25	0	0	0	0	0	0	0	0	0	0	.	.	.	.	.	.
26	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
27	0.12	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0.17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
29	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0.20	0	0	0	0	0	0	.	.	.	.	.	.	.	.	.
31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0.03	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
34	0	0	0	0	.	.	.	.	.	.	.	.	.	.	.	.
35	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
36	0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0.19	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
38	0.06	0.06	0.07	0.04	0	0	0	0	0	0	0	0	0	0	0	0
39	0.03	0.04	0	0	0	0	0	0	0	0	0	0	0	0	0	0
40	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.

Notes:

The entries are the unconditional probabilities of observing a spell of K consecutive price changes, K = 2,...,17. See the text for details. A missing value at CK indicates that there were no data on price changes for more than K consecutive months.

TABLE A4: CONSECUTIVE PRICE CHANGES: MEAT PRODUCTS

STORE	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
1	0.03	0.14	0.19	0	0	0.10	0	0	0	0	0	0	0	0	0	0
2	0.31	0	0.11	0	0	0	0	0	0	0	0	0	0	0	0	0
3	0.18	0.18	0.13	0.13	0	0	0	0	0	0	0	0	0	0	0	0
4	0.33	0	0	0	0	0	.	.	.	.	.	.	.	.	.	.
5	0	0.50	0	0	0	.	.	.	.	.	.	.	.	.	.	.
6	0.18	0.15	0.07	0	0	0	0	0.20	0	0	0	0	0	0	0	0
7	0.22	0	0	0	.	.	.	.	.	.	.	.	.	.	.	.
8	0.50	0	0	0	.	.	.	.	.	.	.	.	.	.	.	.
9	0.18	0.19	0.19	0	0	0	0	0	0	0	0	0	0	0	0	0
10	0.17	0.10	0	0	0	0	0	0	0	0	0	0	0	0	0	0
11	0.13	0.27	0.22	0.29	0	0	0	0	0	0	0	0	0	0	0	0
12	0.08	0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
13	0.47	0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0
14	0.23	0	0	0.07	0	0	0	0	0	0	0	0	0	0	0	0
15	0.36	0.22	0	0.20	0	0	0	0	0	0	0	0	.	.	.	.
16	0.15	0.08	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0
17	0	0	0	0	0	0	0	0	0	0	.	.	.	.	.	.
18	0.29	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0
19	0.16	0.17	0.31	0.09	0.14	0	0.17	0	0	0	0	0	.	.	.	.
20	0.29	0.29	0	0	0	0	0	0	0	0	0	0	0	0	0	.
21	0.14	0	0	0.33	0	0	0	0	0	0	0	.	.	.	.	.
22	0.20	0	0	0	0	0	0	1.00	.	.	.	.	.	.	.	.
23	0.18	0.29	0	0	0	0	0	0	0	0	0	0	0	0	0	0
24	0.25	0.50	0	0	0	0	0	0	0	.	.	.	.	.	.	.
25	0.30	0.14	0.20	0.25	0	0	0	0	0	0	0	0	0	0	0	0
26	0.22	0.14	0	0	0	0	0	0	0	0	0	0	0	0	0	.
27	0.17	0	0.11	0	0	0	0	0	0	0	0	0	0	0	0	0
28	0.20	0	0.17	0	0	0	0	0.50	0	0	0	0	0	0	0	0
29	0.17	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
30	0.30	0	0.33	0	0	0	0	0	0	0	0	0	0	.	.	.
31	0.10	0.14	0.20	0	0	0	0	0	0	0	0	0	0	0	0	0
32	0.20	0.14	0	0	0	0	0	0	0	0	0	0	0	0	0	0
33	0.21	0.11	0.10	0.05	0	0	0	0.17	0	0	0	0	0.17	0	0	0
34	0.18	0.05	0.07	0	0	0	0	0	0	0	0	0	0	0	0	0
35	0.15	0	0.24	0.13	0	0	0	0	0	0	0	0	0	0	0	0
36	0.31	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
37	0.15	0	0.29	0	0	0	0	0	0	0	0	0	.	.	.	.
38	0	0.13	0	0	0	0	0	0	0	0	0.50	0	0	0	0	0
39	0.04	0.28	0.36	0	0	0	0	0	0	0	0	0	0	0	0	0
40	0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
41	0.09	0.09	0.04	0.09	0	0.06	0.07	0	0.14	0	0	0.14	0	0	0	0
42	0.40	0.14	0	0.25	0	0	0	0	0	0	.	.	.	.	.	.
43	0.11	0.13	0.06	0.20	0	0	0.05	0	0.11	0	0	0.13	0	0	0	0
44	0.38	0.20	0.25	0	0	0	0	0	0	0	0	.	.	.	.	.
45	0.12	0.20	0.04	0.16	0.06	0.13	0	0	0.11	0	0	0	0	0	0	0
46	0.25	0.15	0.25	0.17	0.25	0	0	0	0	0	.	.	.	.	.	.
47	0.13	0	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0

TABLE A4: (continued)

STORE	C2	C3	C4	C5	C6	C7	C8	C9	C10	C11	C12	C13	C14	C15	C16	C17
48	0.12	0.10	0.13	0.07	0.16	0.06	0	0	0.10	0	0	0	0	0	0.13	0
49	0.09	0.11	0.30	0.05	0.17	0	0	0.17	0	0	0	0	0	0	0	0
50	0	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
51	0.18	0.08	0.05	0.06	0	0	0	0	0	0	0	0	0	0	0	0
52	0.25	0.11	0.16	0.04	0	0	0	0	0	0	0	0	0	0	0	0.17
53	0	0	1.00	0	.	.	.	.	.	.	.	.	.	.	.	.
54	0.13	0.19	0.06	0.13	0.10	0.20	0	0	0	0	0	0	0	0	0	0
55	0.23	0.07	0.10	0	0	0	0	0	0	0	0	0	0	0	0	0
56	0.20	0.20	0.10	0	0	0	0	0	0	0	0	0	0	0	0	0
57	0.13	0.20	0.14	0	0	0.33	0	0	0	0	0	.	.	.	.	.
58	0.31	0	0	0	0	0	0	0	0	0	0	0	0	.	.	.
59	0.25	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
60	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.	.
61	0.28	0	0.56	0	0	0	0	0	0	0	0	0	0	0	0	0
62	0.23	0.13	0	0	0	0	0	0	0	0	0	0	0	0	0	0
63	0.26	0	0	0.13	0.33	0	0	0	0	0	0	0	0	0	0	0
64	0.11	0	0	0	0	0	0	0	0	0	0	0	0	0	0	0
65	0.17	0.16	0.13	0	0.13	0	0	0	0	0	0	0	0	0	0	0
66	0.08	0.24	0.14	0.18	0	0	0	0	0	0	0	0	0	0	0	.
67	0.39	0.14	0	0	0.11	0	0	0	0	0	0	0	0	0	0	.
68	0.13	0.11	0.08	0	0	0	0	0	0	0	0	0	0	0	0	0
69	0.17	0.31	0	0	0.13	0	0	0	0	0	0	0	0	0	0	0
70	0.21	0.22	0	0	0	0	0	0	0	0	0	0	0	0	0	0
71	0	0.25	0	0.50	0	0	0	.	.	.	.	.	.	.	.	.
72	0.04	0.03	0.09	0.09	0.07	0.13	0.14	0.13	0	0	0	0	0	0	0	0
73	0	0	0	0	0	.	.	.	.	.	.	.	.	.	.	.
74	0.20	0.13	0.16	0	0	0	0	0.20	0	0	0	0	0	0	0	0
75	0.20	0.07	0.10	0.05	0.08	0	0	0	0	0	0	0	0	0	0	0
76	0.20	0.29	0.18	0	0	0	0	0	0	0	0	0	0	0	0	0
77	0.23	0.03	0.08	0	0	0	0	0	0	0	0	0	0	0	0	0
78	0.11	0.08	0.11	0.11	0	0.17	0	0	0	0	0	0	0	0	0	0
79	0.19	0.11	0	0.18	0	0.14	0	0	0	0	0	0	0	0	0	0
80	1.00	0	0	.	.	.	.	.	.	.	.	.	.	.	.	.
81	0.20	0.17	0.22	0	0	0	0	0	0	0	0	0	0	0	0	0
82	0.17	0	0	0	0	0	0	0	.	.	.	.	.	.	.	.
83	0.14	0	0.33	0	0	0	0	0	0	0	0	0	0	0	0	0
84	0.09	0.13	0.09	0.09	0.06	0	0.13	0	0	0.13	0	0	0	0	0	0
85	0.09	0.07	0	0.09	0	0	0	0	0	0	0	0	0	0	0	0
86	0.22	0.09	0	0	0	0	0	0	0	0	0	0	0	0	0	0
87	0.17	0.08	0	0	0	0	0	0	0	0	0	0	0	0	0	0
88	0.13	0	0.25	0	0	0	0	0	0	.	.	.	.	.	.	.
89	0.25	0	0	0	0	0	.	.	.	.	.	.	.	.	.	.
90	0	0	0	0	0	0	1.00	0	.	.	.	.	.	.	.	.

Notes: See notes to Table A3.

TABLE A5: RATIO OF CONDITIONAL PROBABILITIES

WINES

$$\frac{P_{10}}{P_{11}} = \frac{Prob\{X_t = 0/X_{t-1} = 1\}}{Prob\{X_t = 1/X_{t-1} = 1\}}$$

TIME	PROD1	PROD2	PROD3	PROD4	PROD5	PROD6	PROD7	PROD8	PROD9
3	2.0	.	.	0	1.0	∞	∞	0.0	∞
4	∞	.	∞	1	∞	1.0	∞	0.5	∞
5	0.0	0.0	.	∞	∞	1.0	.	2.0	∞
6	∞	∞	.	∞	∞	∞	∞	2.0	∞
7	∞	1.0	1	.	∞	0.0	∞	2.0	.
8	2.7	2.5	∞	5	∞	2.3	∞	∞.0	8
9	2.0	∞	2	1	4.0	3.0	∞	7.0	8
10	3.0	4.0	∞	∞	2.5	4.0	∞	∞.0	∞
11	0.0	0.0	1	0	0.0	0.0	.	1.0	0
12	1.2	12.0	10	2	3.3	5.5	6	5.5	6
13	3.5	∞	1	∞	2.0	∞	0	1.0	3
14	∞	∞	∞	0	2.0	∞	4	∞.0	∞
15	.	.	∞	0	∞	∞	1	.	.
16	∞	0.0	∞	2	∞	∞	∞	2.0	∞
17	∞	0.0	.	∞	.	0.5	∞	0.0	1
18	0.0	1.0	.	.	0.0	0.5	0	2.0	1

$$\frac{Q_{01}}{Q_{11}} = \frac{Prob\{X_{t-1} = 0/X_t = 1\}}{Prob\{X_{t-1} = 1/X_t = 1\}}$$

TIME	PROD1	PROD2	PROD3	PROD4	PROD5	PROD6	PROD7	PROD8	PROD9
3	1.0	.	∞	0.0	1.0	∞	∞	2.0	∞
4	∞	∞	.	0.0	∞	3.0	.	0.5	∞
5	2.0	0.5	.	∞	∞	0.0	∞	2.0	∞
6	∞	∞	∞	.	∞	∞	∞	2.0	.
7	∞	6.0	3	∞	∞	9.0	∞	4.0	∞
8	1.0	2.0	∞	1.0	∞	1.3	∞	∞	8
9	2.5	∞	1	2.0	6.0	1.5	∞	5.0	6
10	0.5	1.0	∞	∞	0.5	1.0	.	∞	∞
11	3.7	13.0	9	8.0	5.5	12.0	∞	12.0	5
12	0.5	2.0	3	0.3	0.3	2.0	0	1.5	1
13	1.0	∞	4	∞	1.0	∞	4	0.5	4
14	.	.	∞	0.0	0.0	∞	1	.	.
15	∞	∞	∞	1.0	∞	∞	1	∞	∞
16	∞	0.0	.	0.0	.	∞	∞	1.0	∞
17	∞	1.0	.	∞	∞	0.5	∞	0.5	2
18	3.7	7.0	∞	∞	4.0	3.0	7	4.0	11

Note: ∞ indicates that the probability in the denominator is zero.
. indicates that estimates of either the denominator or the numerator or both are missing because of lack of observations on that cell.

TABLE A6: RATIO OF CONOITIONAL PROBABILITIES

MEAT PRODUCTS

$$\frac{P_{10}}{P_{11}} = \frac{Prob\{X_t=0/X_{t-1}=1\}}{Prob\{X_t=1/X_{t-1}=1\}}$$

TIME	PROD1	PROD2	PROD3	PROD4	PROD5	PROD6	PROD7	PROD8	PROD9	PROD10	PROD11	PROD12
3	1.25	2.13	7.00	1.33	1.50	7.00	1.00	0.47	0.73	0.35	1.00	1.17
4	0.40	1.20	0.17	1.00	0.75	1.25	0.13	1.56	1.40	0.36	0.33	2.50
5	0.43	1.40	1.00	0.67	2.00	1.17	0.80	0.60	1.50	0.10	0.50	2.00
6	0.94	4.50	1.33	1.00	4.00	2.50	1.00	0.90	1.25	0.53	0.70	*
7	1.20	1.75	0.75	0.20	1.25	0.60	1.20	0.58	1.67	0.50	0.75	4.00
8	0.19	0.33	0.57	0.80	1.00	0.71	1.33	0.33	2.50	0.75	0.30	1.00
9	0.08	0.70	0.60	0.67	1.00	0.40	0.10	0.39	0.13	0.15	0.29	0.07
10	0.57	0.83	1.50	0.80	0.29	0.89	0.58	0.14	0.78	0.57	0.57	0.31
11	0.18	0.17	1.00	2.00	0.67	0.15	1.17	0.61	0.54	0.86	0.50	0.42
12	1.38	2.73	1.00	1.50	*	0.39	1.60	0.91	1.22	0.88	3.25	0.13
13	0.86	1.00	1.67	0.00	1.00	3.00	2.00	0.38	0.83	1.00	1.00	0.15
14	1.40	1.00	2.00	1.75	0.40	2.50	6.00	0.41	2.33	0.00	1.67	0.50
15	0.25	0.27	2.50	2.50	2.00	0.50	1.25	1.09	2.00	1.80	0.83	0.75
16	0.61	3.43	0.75	0.00	1.00	0.18	1.00	0.36	1.17	0.29	0.54	0.08
17	0.71	2.75	0.33	0.30	0.25	0.27	1.29	0.86	1.60	1.60	0.56	0.55
18	1.00	3.00	0.86	0.43	0.38	0.43	0.83	1.57	1.83	7.00	0.86	0.78

$$\frac{Q_{01}}{Q_{11}} = \frac{Prob[X_{t-1}=0/X_t=1]}{Prob[X_{t-1}=1/X_t=1]}$$

TIME	PROD1	PROD2	PROD3	PROD4	PROD5	PROD6	PROD7	PROD8	PROD9	PROD10	PROD11	PROD12
3	4.00	0.38	5.00	1.67	2.00	7.00	1.00	0.18	0.18	0.00	3.00	0.17
4	1.00	1.40	1.33	1.50	1.50	2.25	1.38	0.78	0.60	0.43	1.11	2.00
5	0.57	1.20	0.14	0.33	0.67	1.33	0.40	1.10	1.00	0.29	0.50	1.00
6	0.35	4.00	1.33	1.00	8.00	1.00	0.57	1.00	0.75	0.13	0.40	*
7	1.00	2.00	1.75	0.40	1.00	1.20	0.60	0.67	1.33	0.50	0.75	10.00
8	0.63	1.00	0.14	0.40	0.75	1.00	2.33	0.73	3.00	0.88	0.80	2.20
9	0.50	1.30	1.00	0.33	1.50	0.60	0.80	0.44	1.13	0.50	0.57	0.50
10	0.09	0.75	0.25	0.80	0.57	0.67	0.08	0.32	0.78	0.00	0.07	0.06
11	0.45	1.28	2.00	0.67	0.17	0.69	1.33	0.17	0.73	1.14	0.70	0.42
12	0.08	0.18	0.80	1.00	*	0.11	0.20	0.55	0.22	0.00	0.25	0.33
13	0.71	2.00	1.00	2.00	2.50	0.40	2.50	0.92	0.67	1.67	3.00	0.23
14	1.80	1.38	2.50	0.75	0.40	2.50	6.00	0.35	2.00	0.50	2.00	0.20
15	1.42	1.07	2.00	1.50	1.00	4.00	2.00	0.64	2.00	0.80	1.83	0.63
16	0.28	1.00	1.00	1.60	0.67	0.24	1.67	0.86	1.17	0.86	0.27	0.42
17	0.64	0.00	1.50	0.30	2.00	0.27	0.57	0.50	2.40	0.60	0.56	0.45
18	1.09	7.00	0.13	0.43	0.63	0.36	1.17	1.291	2.00	4.00	1.29	0.67

Note: * indicates that the probability in the denominator is zero.

FIGURE 1: PROPORTION OF PRICE CHANGES
February 1978 - June 1979

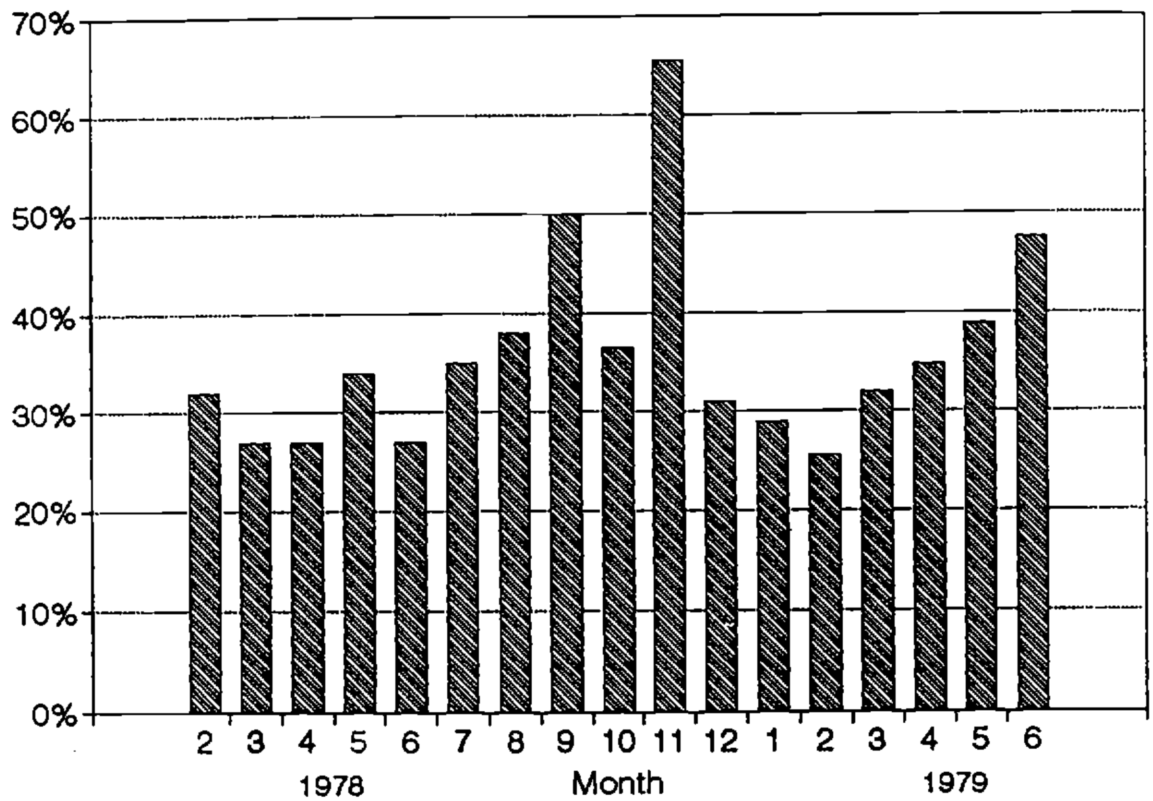
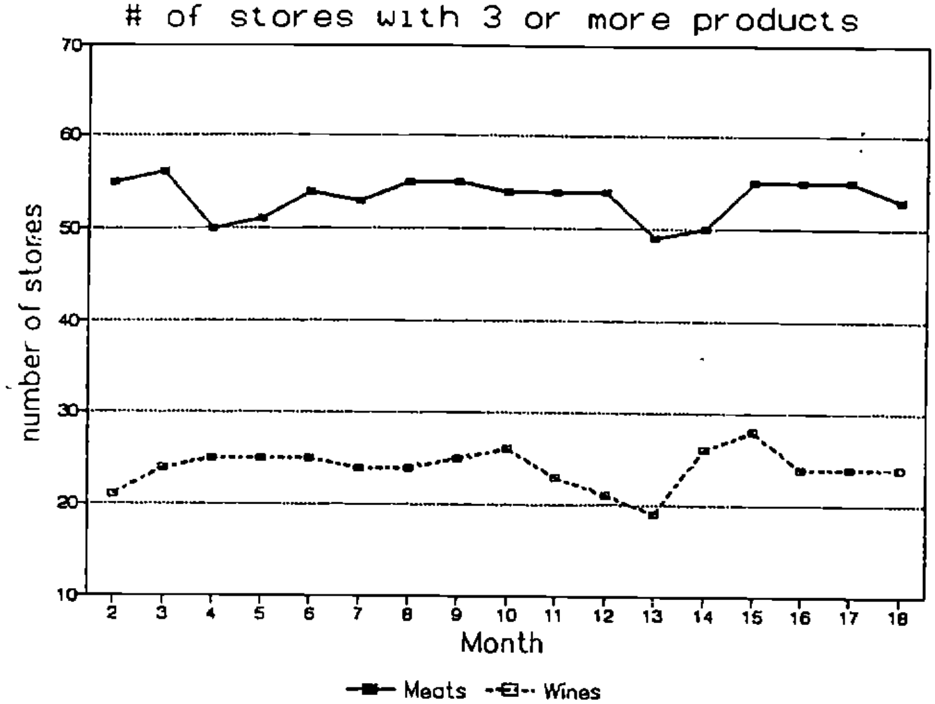


Figure 2: Number of stores and products
February 1978 – June 1979



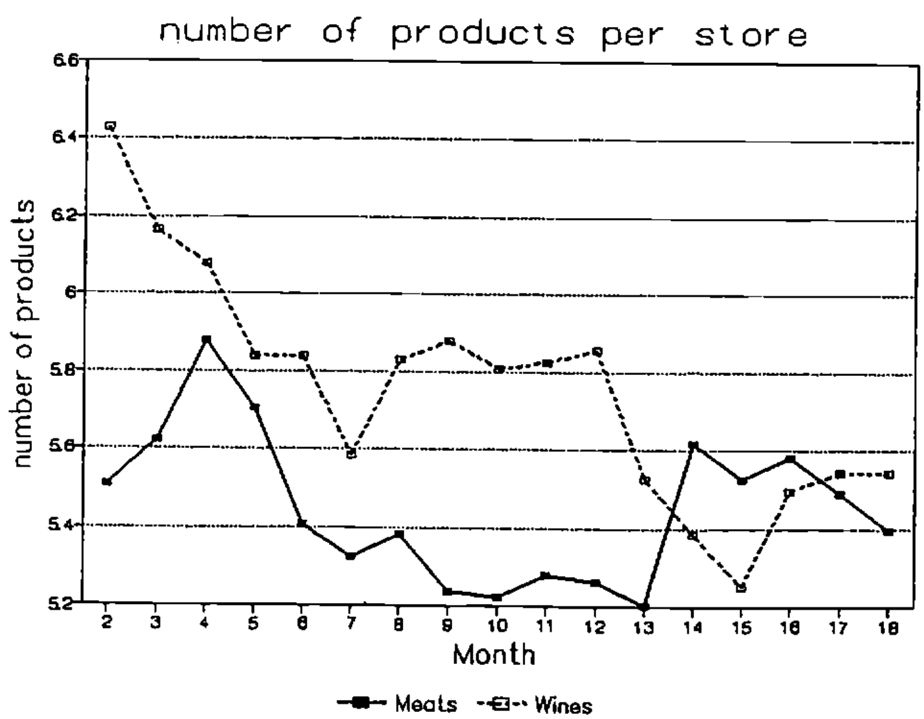


Figure 3. Proportion of Price Changes, Feb. 1978 – June 1979

a. Meat Products

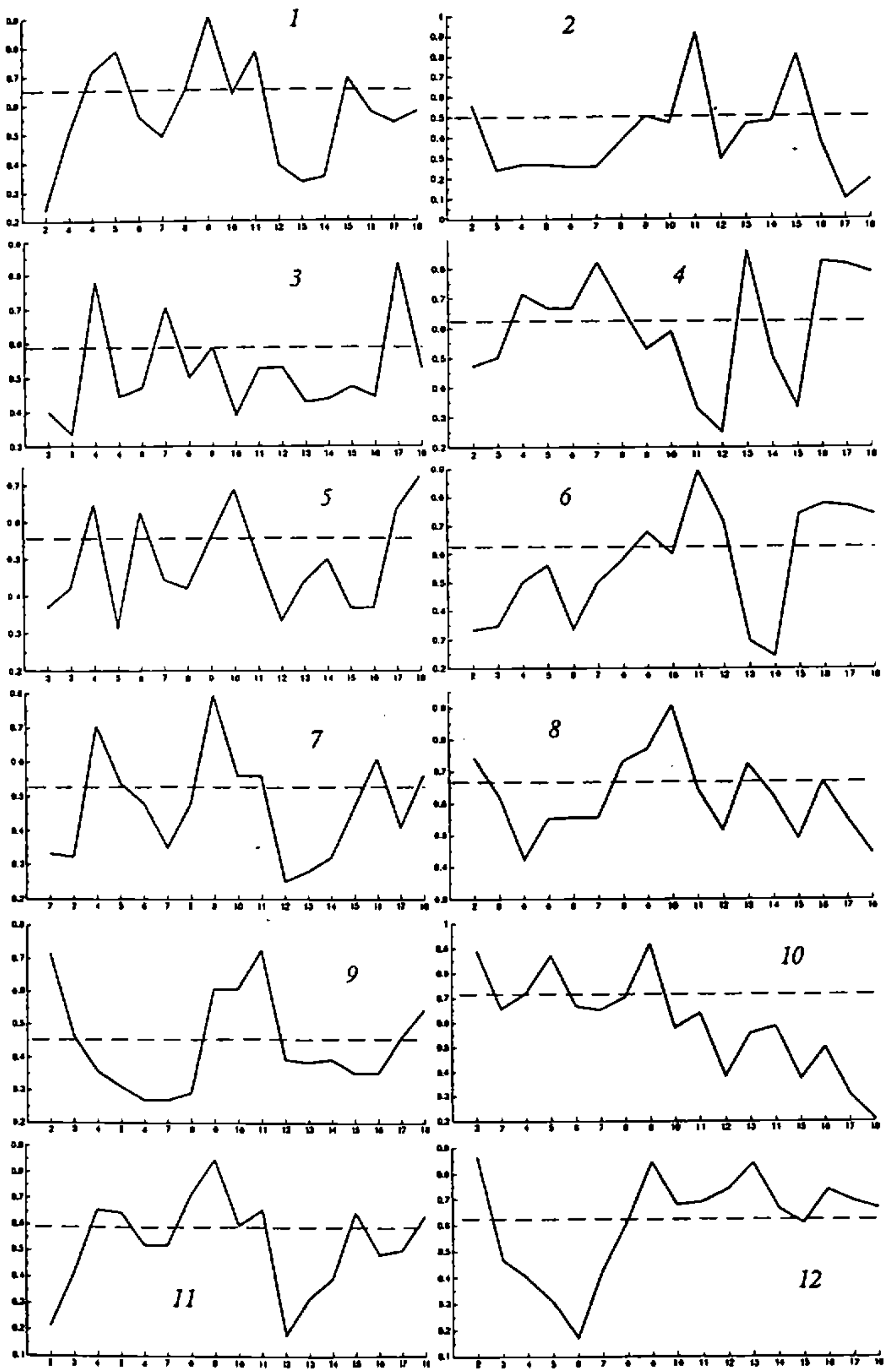


Figure 3. Proportion of Price Changes, Feb. 1978 – June 1979

b. Wines

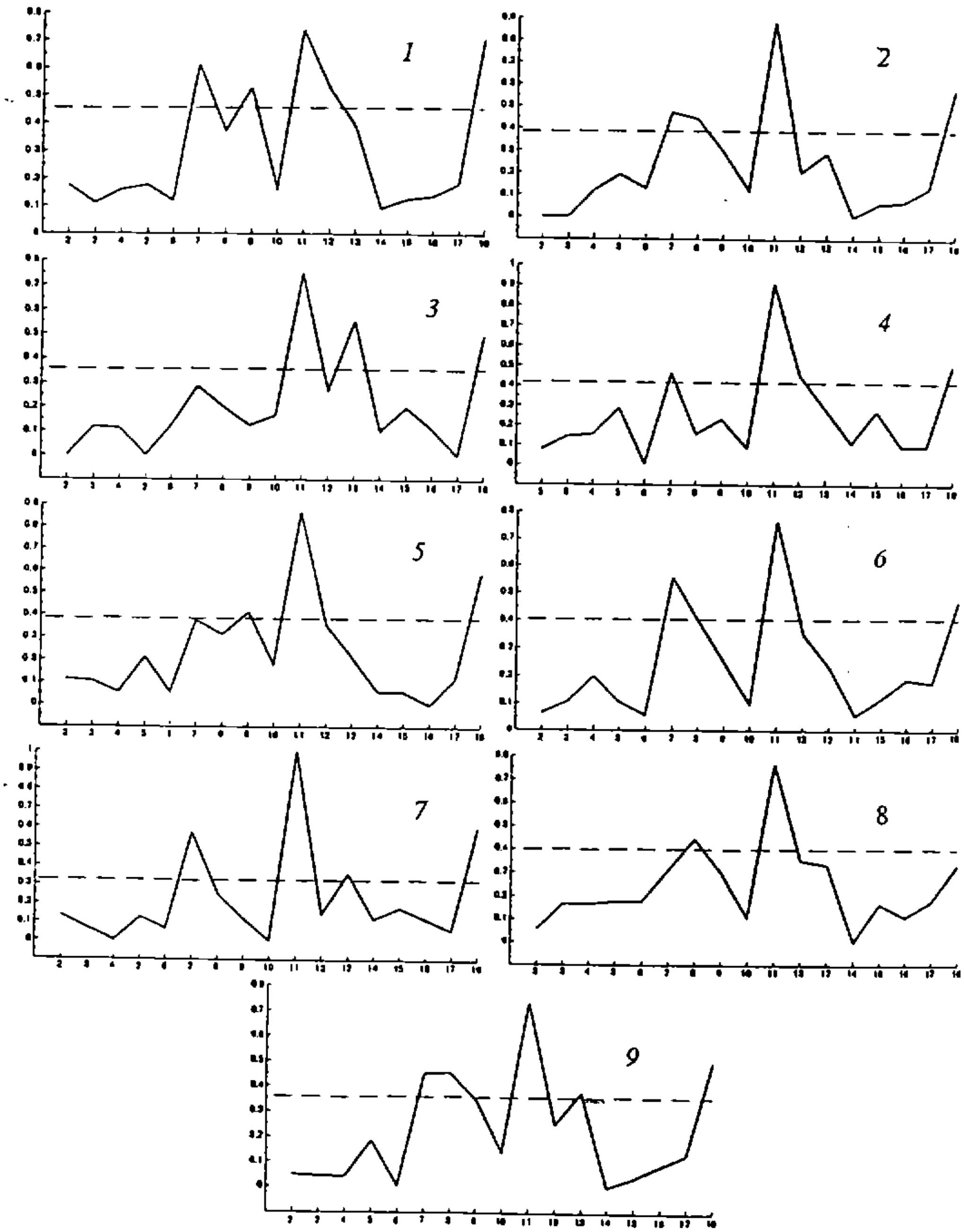


Figure 4: Conditional Probability of a Price Change

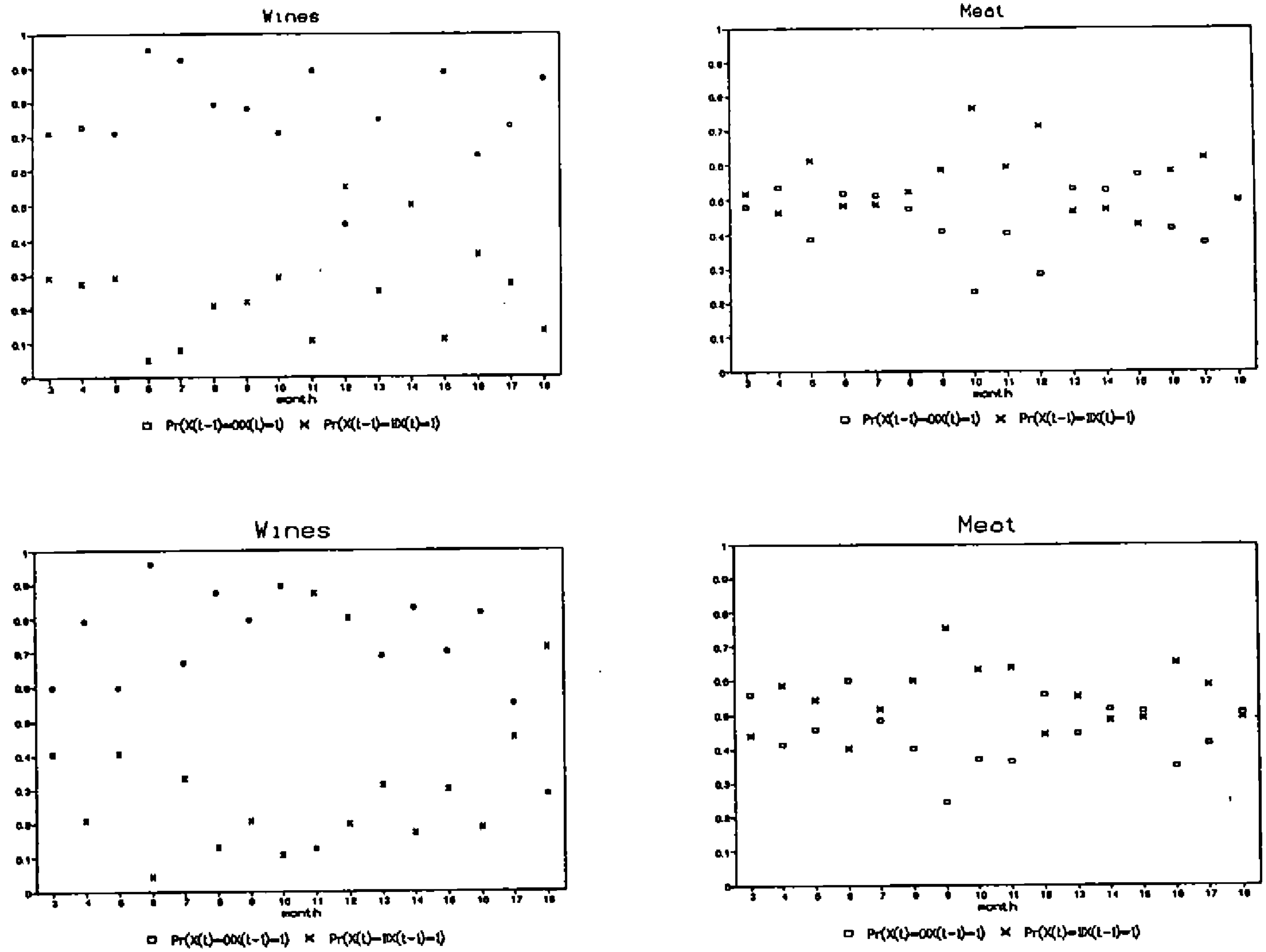
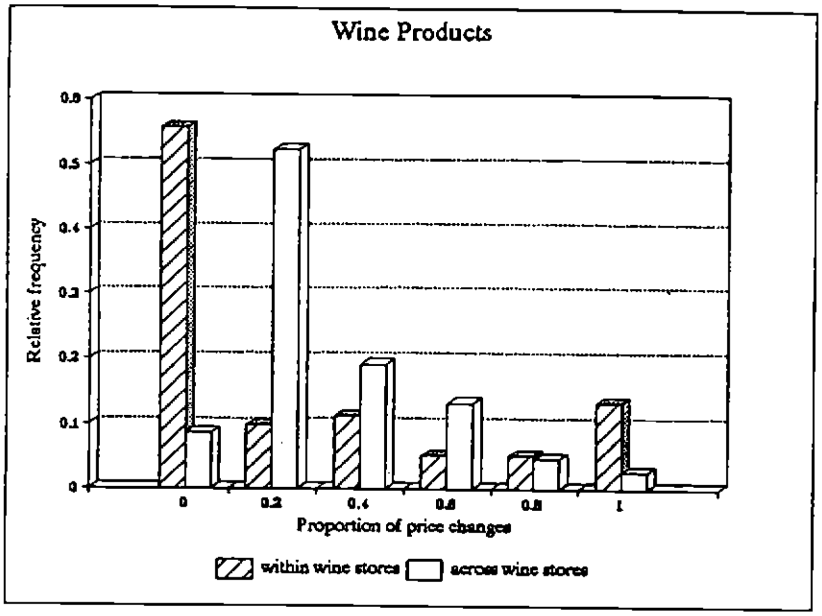


Figure 5: Proportion of Price Changes Within and Across Stores



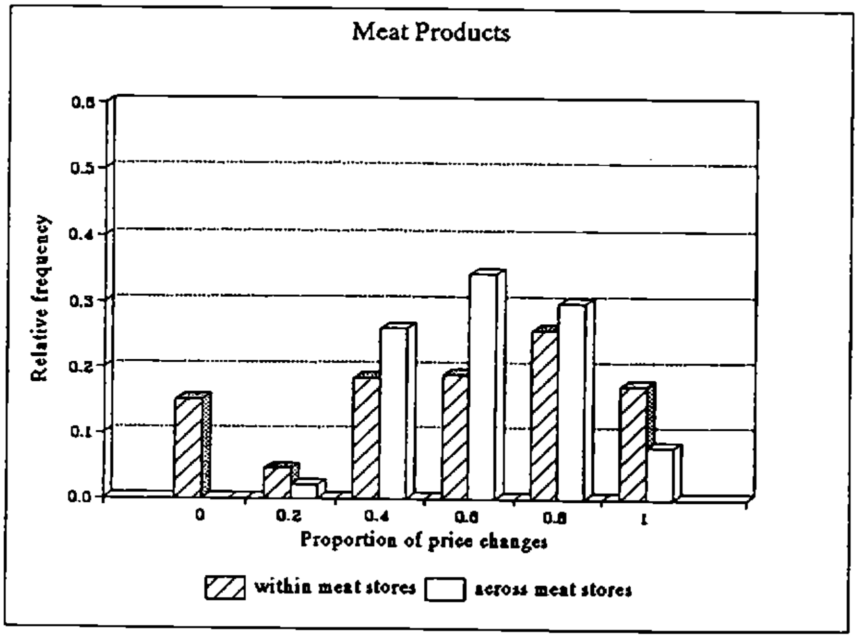


Figure 6: The co-existence of negative
and positive price changes