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# THE SHORT- AND LONG-RUN EFFECTS OF THE VECTOR GROCERY STORE CONSUMER PRICE INFORMATION PROGRAM

by

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## THE SHORT- AND LONG-RUN EFFECTS OF THE VECTOR
## GROCERY STORE CONSUMER PRICE INFORMATION PROGRAM

This paper uses a theory of the way information affects average prices, the price distribution across stores, and the degree of concentration within the retail grocery industry to estimate the effects of Vector Enterprise's consumer information program. Since 1972, Vector has shown each grocery chain's prices on cable television in many cities. By providing consumers with a relatively easy and inexpensive method of comparing prices across grocery chains, Vector's information program has increased the competitiveness of the retail grocery industry in those cities.

The first section of this paper presents a summary of the theoretical model used in this study. The problems of using indexes to provide information about grocery prices are described in the second section. The third section summarizes the major results of previous empirical studies. In the fourth section, Vector's information program is described. The effects of the program on average prices are examined in the fifth section. The sixth section analyzes the impact of the program on the degree of concentration within the retail grocery industry. The effects of the program on the distribution of prices across stores are examined in the seventh section. The last section presents conclusions and suggestions for further research.

## I. Market Perfecting Theory

Economists have long recognized that consumer information about prices is necessary for the efficient and equitable operation of market exchange. As the 1980 Economic Report of the President observed (p. 127), "Increasing the information consumers can draw upon sometimes complements more traditional structural remedies as a means of fostering competition in the market."

Three decades ago, Scitovsky (1950) pointed out that consumer ignorance may be a source of oligopoly (monopoly) power. Later Stigler (1961) developed a model of optimal consumer search behavior across stores. Recent articles by Akerlof (1970) and Diamond (1971) have stimulated renewed interest in the role of information in well functioning markets.

Before examining the consequences of limited information, it is useful to discuss the economics textbook example of a world in which consumers have perfect information. In such a world, consumers will shop at the store which charges the lowest price. If there are no barriers to entry or other distortions such as monopoly power, each store will charge the same price. This price, which equals a firm's marginal cost, is called the full-information competitive price.

No firm has an incentive to raise its price since it faces a perfectly elastic demand curve. A demand curve is called perfectly elastic if, when a store raises its price by the smallest amount, it loses all its customers. Since all consumers know the prices charged by all firms, no firm may charge more than the lowest price in the market.

While such a model is useful for textbook discussions, it is not very realistic. It is more reasonable to assume that consumers have some idea

about the price each store charges, but they do not know the exact price. That is, consumers are not certain about the lowest price in the market or the location of the least expensive store. Under these circumstances, firms will charge a price above their marginal cost.

There are many reasons to believe that consumers have only imperfect estimates of prices charged by a particular store. Grocery and other stores change prices often due to fluctuations in their costs and for other reasons, and consumers typically purchase a large number of different goods in a year. The Progressive Grocer (November, 1974, p. 39) conducted a survey of 560 shoppers in four Providence and Boston area supermarkets in July, 1974. Consumers were asked to cite the selling price of 44 popular brand name and nationally advertised items. Only 24 percent of the shoppers tested knew the " correct" price (within five percent) of a specific product; the comparable figure for a similar study in 1963 was 32 percent.

It is probably true that consumers have an even more difficult time comparing prices across stores. (It should be noted that if prices vary across stores, there may not be a "correct" price as is assumed in the Progressive Grocer study). That is not to say, however, that consumers have no information about relative prices.

According to a report by Burgoyne, Inc. (1977) on the shopping practices of a national cross-section of supermarket shoppers, 64.8 percent read food store advertisements. Almost half (48 percent) of the shoppers reading newspaper ads say that the advertisements influence where they shop. Similarly, 40.7 percent view food store commercials; however, only 15 percent of these television viewers say the commercials influence where they shop.

Approximately two-thirds of the Burgoyne sample compares prices between different supermarkets. The main method for comparative pricing is reading newspaper ads, followed by store visits. The typical consumer shops in 2.06 different supermarkets during a one month period. The average number of supermarkets shopped in during the past week is 1.4. To put that last figure in perspective, it should be noted that the average number of shopping trips is 1.5 per week (although only 31.6 percent of consumers shop more than once a week).

Thus, consumers may obtain price data from a variety of sources and may even have unbiased estimates of the true prices. That is, they do not make consistent errors; they are as likely to overestimate as to underestimate the true price. It is not likely, however, that many consumers will know the exact prices of all items they buy.

As argued above, if consumers know the exact prices charged by all stores, no one store could raise it price and keep any customers. If shoppers have only limited information, stores may raise their prices without necessarily losing all their customers. That is, the demand curve facing each store changes from being perfectly elastic under full information to being somewhat inelastic given limited consumer information.

Firms' demand curves will be inelastic so long as consumers use their estimates of relative prices to choose the store at which they shop. That is, if they treat their price estimates as their best information and go to the store which they believe has the lowest price, they may make a mistake. As a result, a store which raises its price slightly may not lose all its customers, because some of its customers believe (incorrectly) that other stores charge even higher prices.

This model has been formalized in Perloff and Salop (1981). As that paper shows, there are two events which may drive down prices. First, if firms can enter the industry without limit, then (even given imperfect information) prices will be driven down to the full-information competitive price. The presence of significant fixed costs associated with starting a firm, however, will prevent unlimited entry. Government subsidies which offset such fixed costs could increase entry and lower prices.

Second, if consumers' information is improved, prices may be driven down. The intuition behind this result is fairly simple, as illustrated by the following example. Suppose there are only two stores. Store one charges $10 for a given good. Consumers, however, have imperfect information, so that their estimates of the price are not always correct. Initially, one third of all consumers believe that store one charges $9, one third think it charges $11 and the remaining one third estimates the correct price of $10.

Suppose store two charges $10.50. One third of all consumers think it charges $9.50, one third believe it charges $11.50, and the remainder estimate the price correctly at $10.50. Obviously, if consumers form their estimates independently for the two stores, some consumers will shop at store two even though its actual price is higher. That is, some consumers estimate that store one charges $11 and that store two charges $9.50 or $10.50. If there are L consumers, each of whom buys exactly one unit, then store one will sell $(7/9)L$ units and store two will sell $(2/9)L$ units. This example is summarized in the following table:

|           | Share of consumers | | | Sales |
|-----------|--------|---------|---------|--------|
|           | 1/3    | 1/3     | 1/3     |        |
| Store one | $9.00  | $10.00  | $11.00  | (6/9)L |
| Store two | $9.50  | $10.50  | $11.50  | (3/9)L |

Now suppose that the government supplies consumers with better information so that their estimates for the two stores become tighter:

|           | Share of consumers | | | Sales |
|-----------|--------|---------|---------|--------|
|           | 1/3    | 1/3     | 1/3     |        |
| Store one | $9.70  | $10.00  | $10.30  | (8/9)L |
| Store two | $10.20 | $10.50  | $10.80  | (1/9)L |

If store two continues to charge 50 cents more than store one, it will lose half its customers. Before, a customer who correctly estimated the price at store two and overestimated the price at store one would shop at store two. After the information improved so that estimates became closer to the true numbers, such a customer would shop at store one.

As the information improves, store two has an increased incentive to lower its price so that it is closer to that of store one. So long as there is some limit to consumers' information, however, store two can charge more than store one and still retain some customers. But the amount more that it can charge varies inversely with the amount of information consumers have.

This example, is, of course, not fully realistic. It is not true that any improvement in information will lower market price. Information only

helps if it allows consumers to better detect price differences across stores, so that the elasticity of demand facing stores increases. Thus, an increase in information such as that presented in the example will lead to lower prices. Diamond (1971) and others have given examples of increases in information (or reductions in search costs) which do not lead to lower prices.

If useful information is provided to only some consumers, it may actually benefit all consumers. Suppose, for example, that only half the consumers pay attention to some new information about price differences across stores. If they change their behavior so that the demand curves facing stores become more elastic, then consumers who ignore the information will still benefit due to the lowered prices induced by increased competition. Of course, if all consumers use the information, prices will fall more than if only some do.

If only a small proportion of all consumers are informed, however, it is possible that different stores will charge very different prices. Some stores may charge extremely low prices in the hopes of attracting informed consumers (as well as a random sample of the uninformed consumers), while other stores may charge high prices to their uninformed customers. Thus, if only a few consumers become informed, the price dispersion across stores may increase with the advent of an information program (see Perloff and Salop (1981)).

While the discussion has concentrated on prices, consumers base their choice of store on a number of factors in addition to price, such as quality of goods, store location, hours, speed of checkout, and pleasantness of the store. Improved information about quality would have the same effect as information about price. That is, an improvement in information about quality

could lower market price; or, as in the Akerlof (1970) model, make price more related to quality (variety).

Uncertainty about quality is probably not as serious a problem in grocery shopping as in purchasing consumer durables. It is relatively easier to determine the quality of a particular store's meats than to learn how long a used car will last. That is, quality information is rarely a problem in markets where a product is repeatedly purchased and develops a reputation.

Thus, at least in the case of supermarkets, it may be more important to provide information about prices than quality. Consumers may be able to determine quality easily (if it does not change over time), but may not be able to keep up with price changes. Evidence from the Canadian study by Devine and Marion (1979) and the Burgoyne interviews (1977) indicated that price is important to shoppers.

The Burgoyne study asked which characteristic was the most important one in determining where a consumer shopped. The four most common responses were:

| | | |
|---|---|---|
| 1. | Low prices on groceries | 21.7 percent |
| 2. | Quality and freshness of meats | 21.2 percent |
| 3. | Convenient location | 18.5 percent |
| 4. | Attractiveness and cleanliness of store | 13.2 percent |
| | | 74.6 percent |

The same study found that the most common reason given for changing the supermarket where the consumer shopped most often was price (25.6 percent listed this answer, followed by "moved to a different area," given by 23.5 percent of respondents).

To summarize: first, consumers care about prices, but have imprecise esti-
mates of the prices charged by different firms. Second, if consumers have
limited information, stores may raise prices without losing all their cus-
tomers. Third, if some consumers obtain better information so that stores
face more elastic demand curves, stores cannot raise their prices as much.
Fourth, if more customers obtain good information, prices may fall. It is not
necessary for all consumers to rely on the information for it to benefit
everyone, because of the "market perfecting" public good nature of informa-
tion. Fifth, it is possible that if only some consumers become informed that
the price distribution may increase. Some stores may charge only low prices
to attract the inform consumers, but others may charge high prices and sell
only to uninformed customers.

## II.  Indexes

While many economists have argued that increasing consumer information may
have substantial benefits, little attention has been paid to the means of
informing consumers. In most of the large scale experiments to date (dis-
cussed below) and in the Vector program, indexes have been used. Typically,
indexes which are weighted averages of many prices are published in widely
read newspapers, or, in the Vector case, broadcast over cable television
channels. Presumably the idea behind presenting such information is that
consumers are able to infer how prices differ among stores "on average."

There are both benefits and costs associated with using indexes to convey
information. The obvious gain from combining many prices into an index is

that consumers may process and comprehend information more readily in this form. The three major criticisms of indexes are that: (1) indexes are difficult to calculate consistently across stores, (2) they may be "deceptive," and (3) they may lead to collusion among stores.

The first problem, that there may be difficulties in calculating indexes, has been repeatedly raised. This difficulty arises because different stores carry different quality or brand name products. In some markets (e.g., retail gasoline) providing price information by grade of product (octane) and type (regular, unleaded, premium) resolves this problem at the cost of having several indexes (or prices) reported. In grocery stores, where each store carries over 10,000 items, the problem is more difficult to solve. One solution (cf., Purdue/USDA discussed below) is to calculate subindexes. While quality problems may affect the usefulness of meat and fresh produce indexes, indexes of other products may be relatively unaffected by quality variations. Another approach is to identify products by generic type rather than brand name. So long as consumers are aware of possible quality differences across stores (e.g., by being informed of the methodology used to develop the index), these problems may be minimized. The seriousness of these problems can best be examined through empirical experimentation.

This discussion leads naturally to the second problem: due to aggregation or lack of quality comparability across stores, indexes may be "deceptive." That is, consumers may think that the indexes convey different information than they actually do. Thus, indexes are not deceptive in the usual sense, but they may lead to "false reliance" by consumers.

There is an inherent trade-off in forming indexes between simplicity in conveying information and loss of information due to aggregation. Consider

the problem of producing store-specific grocery price indexes. It is not
practical to print a list of 10,000 items' prices for each store and expect
consumers to use such list to decide which store has the lowest prices on the
items they tend to purchase. If, instead, an index (or several indexes) were
published which combined all the prices (or a representative sample) into a
single number, consumers could decide where to shop by simply comparing these
indexes across stores.

A number of issues must be considered in choosing the weights to use in
forming an index and the number of indexes to present. One common method of
combining many prices into a single index is to take a weighted average of the
prices (where the weight for a given good's prices is the amount of money con-
sumers spend on that good divided by their total expenditures). If the
weights used are the ones which a given consumer would use (i.e., this con-
sumer purchases goods in the same proportion as the market as a whole), then
the index effectively condenses the price information into a single number
with no loss of relevant information. The more a consumer differs from the
market average in terms of the percent of expenditures on given goods, the
less valuable such an index will appear to that person if he realizes his
tastes are unusual.

Thus, a person with unusual tastes may ignore the index. However, as was
argued above, if some consumers rely on the index, the consumer with unusual
tastes may still benefit from the resulting lower prices. A more serious
problem arises if the person with unusual tastes improperly relies on the
index. Such a person may think a store has the lowest prices (which is true
for the person with average tastes), while in fact another store has the
lowest prices for a person of his tastes. While this person may benefit from

a lowering of all prices, he would be better off with more detailed information.

One way to make price information more useful to consumers who differ from the average is to publish several indexes. For example, the Purdue/USDA experimental survey (see Boynton, et al. (1981)) published comparative prices in various cities in several ways. Prices of 26 name brand items were listed as well as a total market basket (100 items), index and subindexes for cereal and bakery products; meat, poultry, and fish; dairy and eggs; canned and packaged goods; fresh produce; and non-food items. Given all this information, consumers could choose to rely on the overall index across stores, the subindexes, or specific item prices.

People who find it difficult to compare many prices may choose to rely on the market basket index. Similarly, consumers with "average" tastes could rely on such an index. Consider, however, a vegetarian. If the overall index contains meat prices, such a person may hesitate to rely on that index, unless she had independent information about meat prices across stores (say from advertising, experience, inspection, or other sources). Given the availability of several subindexes, however, the vegetarian could examine only those indexes of interest to her.

Thus, one partial solution to the misreliance (or "deception") problem is to provide more information in the form of subindexes. By providing a range of price information, the promulgators of the information will incur greater calculation and printing expenses than if they published a single index. Further, some consumers may be intimidated by an entire page of numbers and ignore all the information. Others may be unable to find the relevant information on the page. These costs of providing many indexes (increased printing

costs and increased difficulty for consumers to process the information) must be weighted against the benefits (less misreliance).

The problem posed by misreliance (deception) is almost certainly over-stated. An index will be harmful only if it misleads consumers in such a way as to cause prices to rise. In this paper, we attempt to show that the Vector program actually lowers average prices. That is, more prices go down than increase under this program. Thus, harm could occur only if, due to unusual tastes, misinformed consumers disproportionately purchase the few goods' whose prices rise, or are unlucky enough to go to one of the few high-price stores under the mistaken impression that it is a low-price store.

There is an alternative to providing many subindexes by types of good. Instead, following the BLS approach of providing different indexes for dif-ferent income groups, price indexes could be targeted for specific income or other classes. Unfortunately, the work of Michael (1979) suggests that such an approach will be unsuccessful. As he points out with respect to consumer price indexes, the differences between groups are small compared to the dis-persion within groups. Moreover, neither type of difference appears to be stable over time.

The third objection posed to providing indexes (or other forms of informa-tion) is that they may facilitate collusive behavior. It has been argued that the existence of a publicly available price index could facilitate actual or tacit collusion by sellers. Successful price collusion requires two elements: agreement on collusive prices and the ability to quickly and cheaply monitor competitors' behavior to detect cheating on the agreement. By defining and reporting a standard market basket index, an information providing agency may facilitate collusion by lowering both costs of colluding.

While this argument might have some merit in certain industries, it would seem unlikely to be important in the grocery market. In that market, monitoring costs are unlikely to be substantially reduced. Major supermarket chains already monitor prices charged by their competitors, at (presumably) low cost. Thus the main aid to collusion would lie in the provision of an index to serve as a pricing target.

If the index does appear to encourage collusion, a simple solution may be to not announce the components of the index or to randomly change them weekly. In the latter case, a potentially colluding firm which observed that its competitors' indexes were lower than the agreed-upon level would be unsure whether the low value was due to a statistical artifact of the sampling procedure or represented a defection from the agreement.

While the Canadian experiment (discussed below) indicated that the major chains were able to increase their share of the market in the presence of a published index, this result is probably a short-run phenomenon. In the long run, an information program may aid entry into the market by reducing the costs new firms face in making their presence and pricing policy known. Further, increased price information, as argued above, increases the demand elasticity each firm faces, which lowers monopoly power. Thus, in the long run, we would expect an information program to increase rather than reduce competition.

III. Previous Empirical Research

Recent large scale social experiments in grocery markets support the hypothesis that providing consumers with comparative grocery store price

information can lower prices. Devine and Marion's (1979) study of an experiment conducted by the Food Price Review Board of Canada estimated that the provision of comparative supermarket price information may lower prices as much as 6.5 percent. A pretest-posttest, control group research design was employed.

There were three phases in the experiment. During phase one (a seventeen week period), supermarket price information was collected in both the control city, Winnipeg, and in the experimental city, Ottawa-Hull. Only during phase two (a five week period) was the information on grocery store prices in Ottawa-Hull published in newspapers and mailed to some consumers. At no time, was the information publicized in the control city, Winnipeg. In the final phase (six weeks), prices were again collected but not disseminated.

Average food prices declined in Ottawa-Hull by 1.5 percent during the first week of phase two, by 3.0 percent the following week, and then remained steady for the next three weeks. During the first week following the end of phase two, prices dropped an additional 2.5 percent. Thus, the total decline over this six-week period was 7.1 percent. Prices in the control market declined by 0.6 percent in the phase two period; so the differential decrease in the experimental city was approximately 3.9 percent during the five week phase two period and 6.5 percent during the six week period which included the first week of phase three.

Average retail food prices in the test market began to rise within two weeks after the termination of the information program and increased 8.8 percent by the end of the research period. One interpretation of these results is that during the information period, a once-and-for-all drop in average prices occurred. With the end of the information program, prices increased. The test market basket of goods was 2 percent higher than that in the control

market at the beginning of the information program. During the final week of the monitoring program, prices were 1.3 percent lower in the test market. Thus, it is possible that prices in the experimental city had not completely caught up with prices in the control city by the end of the phase three monitoring period.

Devine and Marion also found that higher priced stores' (and chains') prices fell more than those of initially low priced stores. The difference in price index levels between high and low priced stores dropped from a maximum of 15 percent during the preinformation period to a low of 5.4 percent at one point in phase two. The differential for chains fell from a maximum of 7.3 percent to a low of 3.1 percent. The average range of prices during the twelve week period prior to the information program was 9.71 percent compared to 7.83 percent during phase two. The decline in the dispersion of prices was statistically significant at the 90 percent level based upon an F-test of the difference in normalized variances.

A consumer survey indicated that consumers switched in favor of low priced stores. As a result of this shift, the top four corporate chains increased their share of the market from 74 percent to 81 percent.

Other similar Canadian experiments are described in Devine (1978). Apparently the Edmonton and Saskatchewan experiences were not as clear-cut as the Ottawa-Hull experiment.

A more recent Purdue-USDA experiment conducted in four pairs of U.S. cities found declines from 0.2 to 3.7 percent in the relative prices of experimental versus control markets (Boynton, et al. (1981)). In three out of the four experimental cities, a statistically significant decline in the prices of the 26 items which were individually reported was found. Similarly,

in three out of four cases, a statistically significant decline was found in the prices of the 74 items which were included in the total index but were not individually reported (and hence stores may not have known that these items were included in the index). In all four experimental cities, a statistically significant decline in the total (100 item) index was found.

No consistent effect on the dispersion of prices across stores was found. According to consumer surveys conducted before and after the reporting period, consumers' perceptions of high and low-priced stores changed, but in the short span of 6 to 12 weeks no significant store patronage changes occurred.

While these two experiments employed good designs, they were brief programs and they relied on newspapers to disseminate the information. The research reported in this report deals with a long-term information program which utilized an alternative delivery system--cable television. The existence of an effective delivery alternative to newspapers is extremely important given the susceptibility of newspapers to economic pressure brought by grocer advertisers. The present study evaluates the long-run impacts of price reporting, and the use of alternative distribution media.

IV. The Vector Program

Since 1972, Vector Enterprises has been providing consumers with grocery store price information on a chain or store level. To date, Vector has provided this information over cable television in seventeen cities, including Los Angeles, San Diego, Honolulu, Long Island, Manhattan, Arlington, and Topeka. In several of these cities, the programs lasted a year or less, while in Los Angeles, the program has been in existence for over nine years.

In most cities, 80 items are surveyed per store each week, with part of that list rotating weekly among three or four sub-baskets. The marketbasket is not the same in all cities. Vector uses weights based on serving sizes rather than the standard Laspeyres weights (as are used in the Bureau of Labor Statistic's (BLS) Consumer Price Index (CPI) for Food).

In addition to providing an overall index, Vector provides meat, produce, grocery, and sundries (non-food) subindexes, as well as prices on some specific items. Thus, Vector's program is not particularly vulnerable to several of the criticisms of indexes cited above. Consumers with unusual tastes may choose to rely on either some of the subindexes or individual items' prices rather than the overall index. One could argue, however, that due to the unusual weights used by Vector (which are not well-publicized), the indexes may mislead consumers. That is, a consumer may believe, on the basis of the Vector index, that prices in store 1 are lowest; whereas, on the basis of standard Laspeyres weights, they are lowest in store 2.

Vector Enterprises generously provided us with a computer tape containing the prices of individual items by store they collected on a weekly basis through the end of 1979. They also supplied us with the weights they used. We used this information to calculate the indexes they broadcast. When a price was missing in a particular store in a given week, we followed Vector's standard procedure of substituting the average city price for that item in that week. The cable television stations which broadcast the Vector information provided us with monthly figures on the number of consumers subscribing to their systems by month.

## V.  The Effect of the Vector Program on Average Prices

Probably the most important question about the Vector program from a policy standpoint is its effect on average grocery store prices.  If the program lowers average prices, then even if most consumers do not rely on the Vector information, they may, nevertheless, benefit from the existence of the program.  Of course, if the range of prices expands and the percent of relatively high price stores increase, then uninformed consumers could actually be made worse off.  In this section, we examine the effects of Vector on average price, while the effects of Vector on the distribution of prices is discussed below.

In order to measure the effect of the Vector program on appropriately weighted prices, we used the BLS's city specific food CPI indexes (published by the BLS in "Estimated Retail Food Prices by City," for the sample period) for each city studied.  Their index is based on a basket of 90 food only items, which is similar to Vector's.  It should be noted, however, that the BLS samples only some grocery stores in each city in a given month.  Thus, the BLS index could fluctuate from month to month as relatively low price or relatively high price stores are chosen randomly.  In our regression work, this measurement error is captured by the error term and should not bias our results.

We chose to restrict our study to those cities in which the Vector program had been in effect for over one year and for which we could obtain the other necessary data.  These criteria limit our study to three cities: Los Angeles, San Diego, and Honolulu.

We estimated separate equations for each of the three cities over the period January 1972 through December 1979. According to our data base, the Los Angeles program started in November 1973 and extended throughout the rest of the sample period. The San Diego program started in January 1976 and continued through 1979. The Honolulu program, however, did not begin until January 1977 and ended after January 1979.

Several factors in addition to the Vector program may affect grocery store prices. In general, we expect that prices in a given city should change with the average prices in the nation. After all, the national average reflects changing raw food prices and average markups. Barriers to entry may also affect prices. If grocery store construction costs are higher than the national average in a given city, entry of new firms may be prevented, producing a relative increase in prices in that city.

We hypothesize, then, that prices in city i are a function of the average food prices in the U. S. ($BLS_{US}$), a time trend term ($t$) which captures otherwise unmeasured trends, a variable which indicates whether the Vector program is in effect (VECTOR), a time trend term which measures the length of time the Vector program has been in effect (VECTIME), and relative construction costs (CONST):

(1)   $BLS_i = g(BLS_{US}, t, VECTOR, VECTIME, CONST)$.

We experimented with linear, log-linear, and semilog-linear regression specifications. All produced quite similar results. In this paper, we arbitrarily use equations of the form:

(2)    $\log(BLS_i) = c_0 + c_1 \log(BLS_{US}) + c_2\ t + c_3\ VECTOR$
$\qquad\qquad\qquad + c_4\ VECTIME + c_5\ CONST + an\ error\ term.$

It is possible that the impact of the Vector program is a function of the number of consumers relying on the information. Since the Vector price information was disseminated over cable television, not all consumers in a given city had access to the information. Presumably, the number of consumers who rely on the information is a function of the number subscribing to the relevant cable television system. To capture this effect, we hypothesize that the coefficients of the Vector variables (VECTOR and VECTIME) are a function of the share of households in city i which subscribe to the relevant cable television system (TV SHARE). That is,

$c_3 = u + v\ TV\ SHARE,$
$c_4 = w + z\ TV\ SHARE.$

We are implicitly assuming that the fraction of consumers who rely on the Vector information is a fairly constant fraction over time of those who subscribe to the cable television station. According to Vector, Press Association, Inc. reported a survey which indicated that 21.3 percent of all cable subscribers in Los Angeles use the Vector Shopping Guide program.

Thus, the basic regression equation (2) may be rewritten as:

(3)    $\log(BLS_i) = c_0 + c_1 \log(BLS_{US}) + c_2\ t+ u\ VECTOR$
$\qquad\qquad\qquad + v\ (TV\ SHARE)\ x\ VECTOR + w\ VECTIME + z\ (TV\ SHARE)\ x\ VECTIME$
$\qquad\qquad\qquad + c_5\ CONST + an\ error\ term.$

There are several interaction terms (e.g., (TV SHARE) x VECTOR) in equation (3), due to the (TV SHARE) varying specification of the coefficients on the Vector variables.

Table 1 presents (autocorrelation corrected) estimates of equation (3) for each city. The first variable, $Log(BLS_{US})$, is the logarithm of the BLS's national food CPI index. The second variable, Time Trend, takes on the value one in the first period, and increases by one each month thereafter. The Vector Dummy takes on the value one during the months the Vector information was provided and is zero otherwise. The TV Share variable is the ratio of households which subscribed to the relevant cable television station divided by the total number of households in the city (the latter variable was inter-polated from annual averages using time trends and monthly population data).

Instead of using a single time trend to represent the changing impact of the Vector program over time (VECTIME), we use a broken time trend which allows the effects to vary between earlier and later periods. The Vector Time Trend: First 6 Months term is zero when the Vector program is not in effect. In the first month of the program, it takes on the value of one. The value increases by one through the sixth month of the program. Thereafter, the value is again set equal to zero. The Vector Time Trend: Post 6 Months term is zero when the program is not in effect and during the first six months of the program. In the seventh month, this variable takes on the value seven; and each month thereafter the program remains in effect, it increases by one. We have also used a dummy variable, Post 6 Months Intercept, so that slope of the Vector Time Trend: Post 6 Months term is not constrained. We do not also include the Post 6 Months Intercept interacted with TV Share since that vari-able would be almost perfectly collinear with the included variables.

The Construction Costs relative to U. S. Average variable is the F. W. Dodge construction cost index for each city (which was interpolated from semi-annual data using time trends and monthly national data) divided by the Engineering News Record's national building cost index. The Hawaii Information Program is a dummy variable which takes on the value one when it was in effect, and is zero otherwise.

We view this equation as a reduced form equation in which all the right-hand side variables are essentially exogenously determined. We would have liked to control for the relative growth of demand in the three cities (due to differential population growth) and relative wages for grocery store workers. Unfortunately, we were unable to obtain reasonable, monthly series for these variables. Thus, we have a missing variables problem in the regressions reported below. This problem will only bias our results, however, if the missing variables are correlated with the included variables. We also considered using a measure of concentration in these equations, but since the Vector program affected concentration, as shown below, we omitted this endogenous variable from the equations reported in this section.

An inspection of Table 1 shows that the Vector program had a large, statistically significant effect in San Diego and Los Angeles. The results for Honolulu are ambiguous. We consider each city in turn.

A. San Diego

The Vector information program lowered average food prices in San Diego in the sample period. According to our estimates, shown in the first column of Table 1, the program had an increasingly large effect over time.

Table 1
Regression:  Log of the BLS Food Index

|  | San Diego | Honolulu | Los Angeles |
|---|---|---|---|
| Intercept | .873<br>(.269)* | 1.504<br>(.367)* | .387<br>(.241) |
| Log(BLS$_{US}$) | .821<br>(.059)* | .593<br>(.080)* | .908<br>(.051)* |
| Time Trend | .0016<br>(.00062)* | .0029<br>(.00055)* | .00021<br>(.00070) |
| Vector Dummy | .119<br>(.202) | .121<br>(.420) | .183<br>(.076)* |
| TV Share | -.0027<br>(.0051) | -.0072<br>(.022) | -.040<br>(.017)* |
| Vector Time Trend:<br> First 6 Months | -.344<br>(.160)* | .047<br>(.263) | -.025<br>(.147) |
| TV Share x First 6<br> Months Time Trend | .0081<br>(.0038)* | -.0028<br>(.014) | .0058<br>(.032) |
| Post 6 Months Intercept | -.050<br>(.019)* | -.057<br>(.033)# | -.011<br>(.026) |
| Vector Time Trend:<br> Post 6 Months | -.013<br>(.0088) | .014<br>(.029) | .0068<br>(.0062) |
| TV Share x Post 6<br> Months Time Trend | .00030<br>(.00020) | -.00053<br>(.0014) | -.00055<br>(.00064) |
| Construction Costs relative<br> to U. S. Average | -.030<br>(.106) | .515<br>(.195)* | .014<br>(.036) |
| Hawaii Information Program | --- | .0052<br>(.010) | --- |
| $R^2$ | .994 | .982 | .995 |
| Rho | .513 | .668 | .554 |
| t-statistic for rho | -5.61 | -8.42 | -6.25 |
| Number of observations | 88 | 88 | 88 |

Asymptotic standard errors are shown in the parentheses.

A # indicates that the null hypothesis that the coefficient is not asymptotically statistically significantly different than zero can be rejected at the 0.10 level; while a * indicates that the null hypothesis can be rejected at the 0.05 level.

Not surprisingly, the BLS food index for San Diego increased with the national BLS index. The estimated coefficient on the national BLS index is 0.821, which implies that, holding other variables constant, a 10 percent increase in the national average resulted in a 8.2 percent increase in San Diego's index. This coefficient is asymptotically statistically significantly different from one at the 0.05 level. When the time trend is dropped from the equation, however, the coefficient on this term approaches one. We suspect that it is lower than one in the reported equation due to multicollinearity.

The coefficient on the Time Trend indicates that San Diego's prices increased at 1.9 percent per year relative to national prices over the entire sample period. This trend was offset, however, by the Vector program. In the first half year of the program, the average price fell by more each month.

The asymptotically statistically significant coefficients on the Vector Time Trend: First 6 Months and the TV Share x First 6 Months Time Trend indicate that the logarithm of food prices in San Diego fell relative to the national average by

$$(-0.344 + (.0081 \times TV \ Share_j)) \times j,$$

in the $j^{th}$ (less than or equal to six) month. Thus, in the first month, the average price fell by 2.0 percent, and by the sixth month, prices had fallen by 4.3 percent.

The coefficient on the Post 6 Months Intercept term (-0.050) is asymptotically statistically significant at the 0.05 level, but the coefficients on the Vector Time Trend: Post 6 Months and the TV Share x Post 6 Months Time Trend are not. As a result, the logarithm of the San Diego BLS index was lower by -0.050 each month after the first six. That is, the average price

was 4.84 percent lower from the seventh month through the end of the sample period. Thus, prices fell by more each month through the first six, and then levelled off at 4.8 percent below what they would have been in the absence of the Vector program.

The $R^2$ for the equation is 0.994. That is, over 99 percent of the variation in average food prices in San Diego are explained by the equation. Of course, much of the explanatory power of the equation is due to the national price term.

We conclude that prices were lowered substantially in San Diego by the program. These results indicate that the Vector program's impact on average prices varied over time. In the Candanian experiment, a 6.5 percent drop in prices was observed after only a month and a half of dissemination of relative price information using newspapers and mailings.

The slower drop in average prices in San Diego may be due to fewer consumers receiving the price information over cable television (on average, during the time the program was in effect, 42.6 percent of San Diego households subscribed) than received the information in Canada. Of course, the Canadian stores knew that program would be short-lived, and may have responded accordingly.

This latter point may also explain why the drop in prices was less in San Diego than in Canada. An alternative explanation is that there is more monopoly power in Canada and hence a greater opportunity for prices to fall. Prior to the consumer information program, the four-firm concentration ratio in Ottawa-Hull was 74 percent. The comparable figure for San Diego in the year prior to the start of the Vector program (1975) was 46 percent. Since there were only eight major chains in San Diego, each chain had a roughly equal market share.

B.  Honolulu

None of the Vector variable coefficients in the estimated equation for Honolulu (column 2 of Table 1) was asymptotically statistically significant at the 0.05 level.  The coefficient on the Post 6 Month Intercept term was asymptotically significant at the 0.10 level, however.  If we presume that the other Vector coefficients are essentially zero, that implies that the program had no effect in the first six months, but from the seventh month through the end of the program (in the 25th month), prices were roughly 5.5 percent lower than they otherwise would have been.  Given the imprecision with which this coefficient is measured, some caution should be shown in evaluating this result.  The standard error on the Post 6 Month Intercept's coefficient suggests that we may be 68 percent confident that the reduction in prices lies between 2.4 percent and 8.6 percent.

The term on construction costs in Honolulu relative to construction costs nationally is statistically significant.  Its positive sign indicates that an increase in construction costs in Honolulu relative to costs elsewhere raises food prices in Honolulu (holding national prices constant).  Presumably, this effect reflects the increased market power existing firms have when the cost of entering the market (through building new stores) rises.  There are ten major chains in Honolulu and the four-firm concentration ratio prior to the start of the program was 49.2 percent (in 1976), so the degree of monopoly power was probably limited.  It should be noted, however, that the four-firm concentration ratio fell each year the program was in effect, and reached 44.4 percent in 1979.

The last coefficient, the Hawaii Information Program dummy, refers to a similar consumer information program which was in effect for the first

eighteen months of our sample period. The equation indicates that this program did not have an asymptotically statistically significant effect.

Between April 1969 and June 1973 the Department of Agriculture of the State of Hawaii conducted a consumer grocery store price information program on Oahu. Starting in the spring of 1970, the Honolulu Advertiser began publishing market baskets for specific stores. However, since the method of calculating the market basket totals had been seriously criticized, they were published only in an explanatory section below the price list for individual items; as a result, the market basket totals may have been effectively obscured.

Apparently due to the inaccessibility of the market basket totals to readers, surveys indicated that consumers made little use of the price information. Even so, studies conducted by the Department of Agriculture indicated that after publication of the prices of the Oahu survey items, prices of these items declined and stabilized. However, since twenty-five of the forty items surveyed each week were chosen from a fixed list of seventy items, it is possible that stores determined the identity of those seventy items and maintained low prices on those items while raising prices on other items. Our estimates do not show that the program had a statistically significant effect during its last eighteen months in operation. There is some evidence that by that point, few consumers were actively paying attention to the published results.

### C. Los Angeles

The Vector Program lowered average food prices in Los Angeles. Our equation, shown in column 3 of Table 1, indicates that the program had an

asymptotically statistically significant effect which did not vary over time except to the degree that the TV Share variable changed.

The coefficients on the Vector Dummy and the TV Share variable are asymptotically statistically significant at the 0.05 level. None of the Vector Time Trend terms (or interaction terms) are individually asymptotically statistically significant.

The Vector effect is the sum of the coefficient on the Vector Dummy and the coefficient on the TV Share variable: 0.157 - (0.034 x TV Share). The Vector program raised prices by 0.9 percent in the first month (relative to the national average). By the sixth month, however, the Vector program raised prices by only 0.2 percent. The program was lowering prices from the eighth month on. By the end of the second year, prices were 6.2 percent lower; and by the end of the sample period (in the 66th month of the program), prices were 12.0 percent lower.

According to the equation, this change over time is due to the increased availability of the cable information. When the program started, only 4.4 percent of Los Angeles households subscribed to the relevant cable television system. This figure rose to 7.8 percent by the end of the sample period. That is, over 50 percent more households subscribed after six and a half years. It should be noted, however, that a much lower percentage of households were exposed to the Vector information in Los Angeles than in San Diego or Honolulu. The average in Los Angeles during the period when the Vector program was in effect was 6.5 percent, while the comparable figure for San Diego is 42.6 percent, and for Honolulu is 19.6 percent.

Of course, the slight increase in the first few periods could have been due to collusive behavior on the part of grocery stores. Given the standard errors on our coefficients, it is possible that this slight increase in the early periods is merely a measurement problem. Since there are twenty major

chains in the Los Angeles area, and the four-firm concentration ratio prior to the start of the program was 32.0 percent (in 1972), it is hard to believe that any collusive agreement is possible.

It is striking that the Vector program had a larger effect in Los Angeles than in the other cities given the relatively small number of households exposed to the information program (at most 7.8 percent of all households ever saw the information). If these results are replicated in future research, they may indicate that an effective program can be instituted even with extremely limited information dissemination.

## VI. Vector's Effect on Grocery Store Concentration

As we argued above, firm-specific consumer information may affect market shares. The information program may have several conflicting effects. In one scenario, if consumers rely on the information, they will shop at stores which Vector identifies as having low prices. Until other stores react by lowering their prices, the market share of the initially low-price stores will rise. Eventually, however, as all stores are forced to charge the same (relatively low) price, the market share of the initially low price stores reverts to its earlier level.

In an alternative scenario, firms may initially collude. The information program, by lowering the cartel's costs of enforcing price fixing agreements, may freeze market shares or allow the market shares of noncolluding firms to rise. Regardless of which scenario is the relevant one, it would not be surprising for the effects of the information program to differ over the life of the program.

Because market share data are only available annually, our empirical study of the effects of the Vector program on concentration is based on a relatively small sample. The regression reported in Table 2 represents the combined Los Angeles and San Diego samples (1972-1979). Since concentration data for Honolulu are only available from 1976 on, Honolulu was not included in our sample.

The four-firm concentration ratio (the market share of the four largest firms) was regressed on a time trend, the cable television shares of house-holds in Los Angeles and San Diego during the period in which the Vector program was in effect,[*] and a Vector time trend (the number of months in each year the Vector program had been in effect as of the end of each year) for both cities. If the Vector time trend is multiplied by TV Share, a virtually identical equation is obtained.

The equation "explains" a large percent of the variance in concentration (the $R^2$ = 0.95). All the coefficients are statistically significantly dif-ferent from zero at the 0.05 level except for the coefficient on the share of cable television in Los Angeles. The coefficients on the Vector time trends are negative, indicating that the longer the Vector program was in effect, the lower was the four-firm concentration ratio. Since the coefficients on the share of cable television variables are positive, the combined effect of the two variables indicates that concentration initially rose and then fell in both cities.

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[*] The Vector program did not start in Los Angeles until November 1973, thus, the TV Share variable for 1973 was multiplied by 2/12 since the program was only in effect for two months in that year.

## Table 2

### Regression on Four-Firm Concentration
### for Los Angeles and San Diego

| Variable name | Coefficient | Standard error | t-statistic |
|---|---|---|---|
| Intercept | 28.077 | 2.063 | 13.611 |
| San Diego dummy | 5.996 | 2.218 | 2.703 |
| Time Trend | 2.772 | .937 | 2.959 |
| Cable TV Share in LA | .916 | .530 | 1.729 |
| Cable TV Share in San Diego | .246 | .077 | 3.213 |
| Vector Time Trend for LA | -.191 | .095 | -2.007 |
| Vector Time Trend for San Diego | -.298 | .113 | -2.634 |

$R^2$ = .95
F-statistic = 28.13
Number of observations = 16

Figures 1 and 2 plot the concentration ratios for San Diego and Los Angeles. The dashed line shows the actual concentration ratios, the heavy line shows the estimated concentration ratios, and the light line shows what the estimated concentration ratios would have been in the absence of the Vector program. In both cities, had the Vector program not existed, the fourfirm concentration would have been higher initially and then fallen.

Because of the small sample, limited confidence should be placed in these results (in spite of the large $R^2$). As the plots show, the equation does a good job of estimating the "turning points" in San Diego's concentration ratio, but misses a brief increase in the Los Angeles ratio in 1976 and 1977. Apparently there was a large increase in concentration in both cities in 1976. While the Vector program variables appear to capture this increase in San Diego, they do not in Los Angeles. With more degrees of freedom, we could have used higher order polynomials to fit this equation (as we did in the price equations).

The results of this study are consistent with those obtained in the price equations. Apparently the Vector program increased competition over time. While many theorists and empirical researchers have expected price information programs to have a once-and-for-all effect soon after they are first introduced, these results indicate that even after several years, the impact of the Vector program was still increasing.

The initial increase in concentration in Los Angeles and San Diego is consistent with Devine and Marion's (1979) Canadian results. They found, during the short experimental period, that low price firms' market shares increased. Presumably, after a few months of the program, other firms are forced to match
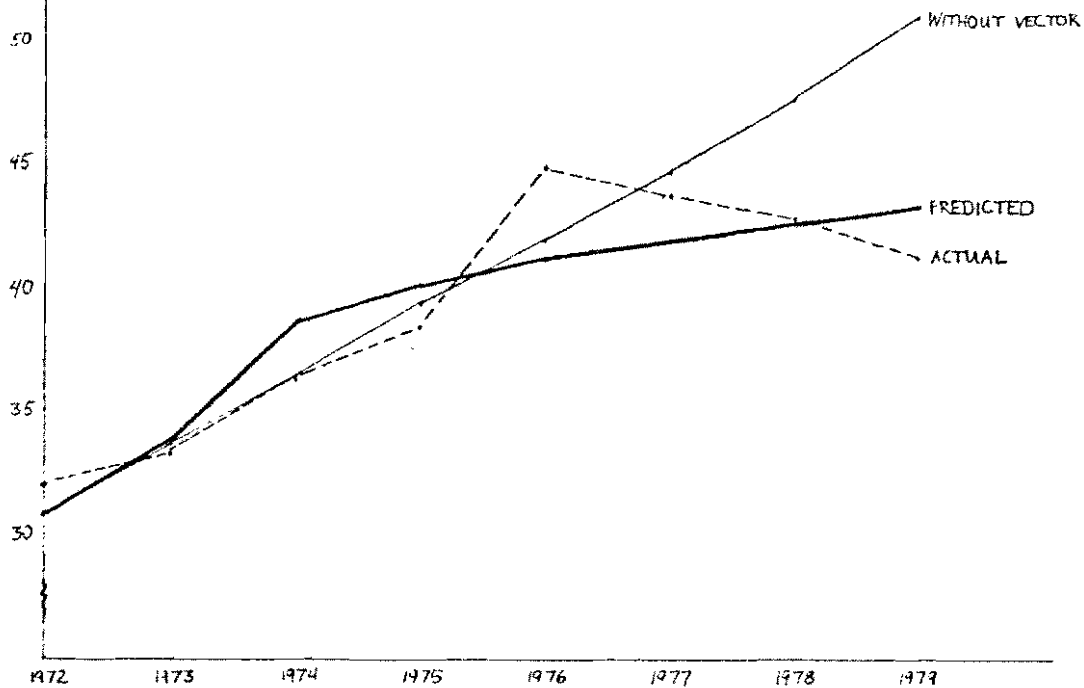
Figures 1 and 2
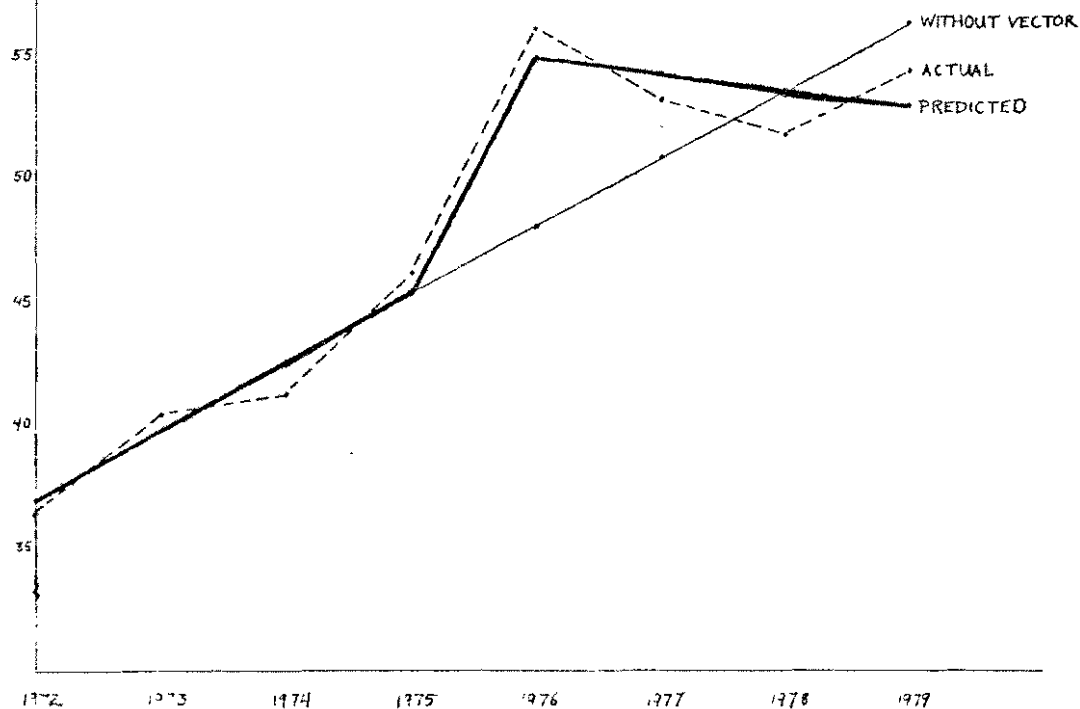


San Diego



Los Angeles

these low prices, and the four-firm concentration ratio falls. One possible alternative explanation for the long-run impact of the program is that the effect of any such information program depends crucially on how widely the information is disseminated. Because of the growth of cable television in the two cities over the sample period, the Vector information may have affected an increasing proportion of all consumers over time. In Los Angeles, the share of households receiving the relevant cable television channel increased by over 75 percent from 4.4 percent to 7.8 percent. In San Diego, the share rose slightly from 39.8 percent to 44.3 percent.

## VII. The Effect of the Vector Program on the Distribution of Prices

The Vector information program affected the distribution of prices, as well as the average price. After examining the data on a weekly and a monthly basis, we believe that the distribution of prices varies in shape over the sample period, but is generally a single peaked function. In order to describe the shape, we fit two-parameter beta distributions to the monthly data (which is the aggregation of the weekly data).

The beta distribution we estimated is

$$f_B(x;p,q) = \frac{1}{B(p,q)} \frac{(x - a)^{p-1}(b - x)^{q-1}}{(b - a)^{p+q-1}} ,$$

where x is the price in each store in a given week during the month, a is the observed minimum price during the sample period, b is the observed maximum price, p and q are the "shape" parameters of the beta, and $B(p,q)$ is the "beta

function." The parameters p and q were estimated using maximum likelihood techniques.

If p and q are both larger than one, then the distribution is single peaked. As p and q increase, the distribution's peak increases. If p and q are equal, the distribution is symmetric; while if p is larger than q, the distribution is skewed to the right (and to the left if q is larger).

To determine how the Vector program affected the distribution of grocery store prices we regressed p and q and the logarithms of a and b on a number of explanatory variables including measures of the dissemination of the Vector price information. This regression methodology should produce consistent, but inefficient estimates. Of course, we can only estimate the effects of the program on these parameters during the period the program was actually in effect, since we do not have Vector price information for any other period. It again should be noted that the store price variable, x, is Vector's serving size weighted price index, which bears little resemblance to traditional Laspeyres indexes.

Since we only have observations for the period when the Vector program was in effect, we can only explain how the distribution parameters change with respect to the degree of dissemination of the Vector information (TV Share and interactive terms). There is no distinction between a general Time Trend term and Vector Time Trend terms since they are perfectly collinear.

The regression results are reported in Tables 3, 4, and 5, for San Diego, Honolulu, and Los Angeles. These equations were estimated using ordinary least squares techniques, except where a rho value is reported which indicates that an autocorrelation correction was made. An increase in the dissemination of the Vector price information appears to have had different effects in the three cities on the distribution of grocery store prices.

A. <u>San Diego</u>

The first column of Table 3 indicates that the degree of dissemination of the Vector information had no measurable impact on the lowest store price observed (a) in a given month. The TV Share variables and the interaction variables did affect the maximum price observed (b).

The elasticity of b with respect to TV Share is 0.044 x TV Share in the first six months and (0.044 - 0.0015 x j) x TV Share in the $j^{th}$ month (where j is greater than 6). The elasticity is 1.75 in the first month which means that a one percent increase in TV Share would have increased the maximum price by 1.75 percent. By the sixth month, the elasticity is 1.82. The elasticity continues to fall over time: it is 1.36 in the seventh month, 0.3 after two years, and -0.7 after 40 months (the end of our sample period). That is, an increase in dissemination would have increased the maximum price in the beginning of the program, but would have decreased it by the end of the sample period.

Apparently, the program did not affect the p parameter in the first six months of the program. Thereafter, p increased with the TV Share over time. The elasticity of p with respect to TV Share is 2.6 in the seventh month, 11.5 after two years, and 18.5 by the end of the sample period. That is, a one percent increase in TV Share would have increased p by 2.6 percent in the seventh month, and by 18.5 percent by the end of the sample period.

Since there are no statistically significant coefficients in the q equation, q does not appear to vary with the degree of dissemination. Thus, since p is an increasing function of TV Share and q is not, an increase in TV Share would shift the distribution to the right. That is, increased dissemination could have led to a larger fraction of relatively high price stores. Since

## Table 3

### Regressions: Beta Distribution Parameters
### San Diego

| Variable name | Log(a) | Log(b) | p | q |
|---|---|---|---|---|
| Intercept | -10.152 (3.738)* | -8.960 (2.495)* | 6.845 (11.060) | 5.877 (8.443) |
| Log (BLS$_{US}$) | 2.787 (.653)* | 2.570 (.436)* | --- --- | --- --- |
| First 6 Months Time Trend | .220 (.595) | .493 (.397) | 3.338 (.897) | 1.724 (7.115) |
| Post 6 Months Time Trend | .033 (.031) | .057 (.021)* | -.944 (.434)* | -.450 (.361) |
| TV Share | .040 (.026) | .044 (.017)* | .072 (.210) | -.051 (.165) |
| TV Share x First 6 Month Time Trend | -.0052 (.014) | -.012 (.010) | -.085 (.215) | -.042 (.172) |
| TV Share x Post 6 Months Time Trend | -.0010 (.0008) | -.0015 (.0005)* | .022 (.010)* | .010 (.0083) |
| Construction Costs Relative to US Average | -.534 (.804) | -.600 (.537) | -6.854 (9.179) | -1.451 (7.258) |
| $R^2$ | .920 | .958 | .219 | .215 |
| Rho | --- | --- | --- | .396 |
| Rho's t-statistic | --- | --- | --- | 2.72 |
| D. W. statistic | 1.86 | 1.91 | 2.37 | --- |
| Number of observations | 40 | 40 | 40 | 40 |

the average value of q over the sample period (1.7) is larger than the average value for p (1.6), the distribution is skewed towards low price stores. Thus, this effect may actually decrease the skewness towards low prices rather than actually cause the distribution to be skewed toward high prices.

These results are somewhat disturbing, since they suggest that if the Vector information had been more widely available, the lowest price available would not have changed, but the maximum price would have increased (at least during the early part of the period) and the distribution would have become more skewed towards the high end. These results indicate that when dissemination increases, an increasing fraction of stores will charge high prices in the hopes of profiting from uninformed consumers. Only limited confidence can be placed in these results, however, since we only have information during the period Vector's program was in effect, and the price indexes used by Vector differ subtantially from standard indexes.

B.  Honolulu

The equations shown in Table 4 suggest that an increase in dissemination would have greatly lowered the minimum (a) and the maximum (b) prices during the first six months, but the effect is statistically insignificant there-after. The elasticities on a and b with respect to TV Share are -1.4 and -1.7 in the first month. That is, a one percent increase in TV Share in the first month would have decreased a by 1.4 percent and decreased b by 1.7 percent. These negative effects are even more pronounced in the next few months, but apparently die out after the first half year.

The TV Share has a statistically significant, positive effect on p, but does not have a statistically significant effect on q. The elasticity of

## Table 4

### Regressions: Beta Distribution Parameters
### Honolulu

| Variable name | Log(a) | Log(b) | p | q |
|---|---|---|---|---|
| Intercept | -.166 (3.278) | -.631 (2.499) | -55.680 (19.959)* | -25.390 (20.219) |
| Log (BLS$_{US}$) | 1.143 (.499)* | .722 (.370)# | --- --- | --- --- |
| First 6 Months Time Trend | 1.422 (.603)* | 1.631 (.528)* | 11.769 (10.928) | .711 (11.070) |
| Post 6 Months Time Trend | -.016 (.028) | -.028 (.024) | -.155 (.508) | -.178 (.514) |
| TV Share | -.017 (.048) | .015 (.037) | 1.672 (.708)* | .155 (.717) |
| TV Share x First 6 Month Time Trend | -.076 (.033)* | -.089 (.029)* | -.641 (.591) | .045 (.599) |
| TV Share x Post 6 Months Time Trend | .0012 (.0015) | .0015 (.0012) | .00035 (.025) | .0079 (.026) |
| Construction Costs Relative to US Average | -.537 (.732) | 2.029 (.565)* | 28.976 (13.666)* | 26.662 (13.845)# |
| $R^2$ | .966 | .971 | .395 | .310 |
| Rho | -.105 | .389 | --- | --- |
| Rho's t-statistic | -.52 | 2.07 | --- | --- |
| D. W. statistic | 1.67 | --- | 2.56 | 2.39 |
| Number of observations | 25 | 25 | 25 | 25 |

p with respect to TV Share is quite large; on average over the period, it is 19.3. That is, a one percent increase in dissemination would have increased p by 19.3 percent. Since on average, p and q are equal during the sample period (1.7), the distribution would become skewed to the right if dissemination increased. Because this effect is offset by a decrease in the minimum and maximum prices in the early periods, the distribution would first shift toward lower prices and then become skewed towards higher prices near the end of the program.

An increase in relative construction costs would increase the maximum price. It would also increase both p and q, causing the distribution to become more peaked. Presumbably this effect reflects increased barriers to entry.

### C. Los Angeles

The results in Los Angeles are more consistent with the results obtained in our price equations, as shown in Table 5. The minimum price (a) would have been lowered substantially by an increase in dissemination. The elasticity of a with respect to TV Share is -3.2 in the first period, -0.7 in the seventh period, -1.4 in the 24th month, and -3.4 at the end of the sample period (the 66th month). That is the elasticity is very large (in absolute value) in the early months and then is smaller in later months (but grows again towards the end of the sample period).

An increase in dissemination would have lowered the maximum price substantially in the first few months, but would not have had a statistically signficant effect thereafter. The elasticity of b with respect to TV Share is -1.5 in the first month and then grows to -9.1 by the sixth month.

An increase in dissemination would have lowered both p and q substantially. The elasticities are -10.3 and -8.0 for p and q in the first

Table 5

Regressions: Beta Distribution Parameters
Los Angeles

| Variable name | Log(a) | Log(b) | p | q |
|---|---|---|---|---|
| Intercept | -.421 (1.652) | -1.414 (1.690) | 7.633 (5.561)* | 20.787 (13.374) |
| Log (BLS$_{US}$) | 1.103 (.328)* | 1.412 (.335)* | --- --- | --- --- |
| First 6 Months Time Trend | 2.804 (.851)* | 1.513 (.855)# | 14.738 (7.336)* | 27.789 (17.642) |
| Post 6 Months Time Trend | .047 (.019)* | .0034 (.019) | .273 (.154)# | .979 (.371)* |
| TV Share | -.115 (.062)# | -.0018 (.063) | -.811 (.458)# | -3.060 (1.101)* |
| TV Share x First 6 Month Time Trend | -.607 (.185)* | -.331 (.186)# | -3.166 (1.597)# | -5.941 (3.841) |
| TV Share x Post 6 Months Time Trend | -.0048 (.0019)* | -.00011 (.0019) | -.025 (.016) | -.095 (.038)* |
| Construction Costs Relative to US Average | .100 (.223) | -.102 (.225) | -1.222 (1.720) | -2.270 (4.136) |
| $R^2$ | .886 | .894 | .307 | .173 |
| Rho | -.368 | -.390 | --- | --- |
| Rho's t-statistic | -3.21 | -3.44 | --- | --- |
| D. W. statistic | --- | --- | 1.80 | 1.68 |
| Number of observations | 66 | 66 | 66 | 66 |

month, -1.6 and - 3.1 in the seventh month, -4.3 and -12.8 after two years, and -3.7 and -19.3 by the end of the sample period. That is, initially an increase in TV Share would cause p to fall relative to q, while in later months, q would fall relative to p. Since both p and q are reduced by an increase in TV Share, the price distribution becomes less peaked. Initially it would become more skewed to the left (toward low prices). After a couple of years, the distribution would become more skewed to the right (though relatively flat).

D. Summary

Unlike the price and concentration equations, these results are hard to interpret. In Los Angeles and Honolulu, an increase in the dissemination of the Vector information would have substantially lowered both the minimum (a) and maximum (b) prices during the first few months. That is, the entire distributions would have been shifted towards lower prices. In Los Angeles, this effect continues throughout the sample period. The San Diego equation implies that the distribution would shift towards higher prices given an increase in dissemination. It should be noted, however, that this effect is reversed towards the end of the sample. It is possible (especially given the negative, though asymptotically statistically insignificant coefficents on the TV Share x time trend terms) that we would have found a downward shift earlier in the period if we had more precise estimates.

In all three cities, there is some evidence that an increase in dissemination would have skewed the distribution of prices (given the minimum and maximum prices) towards higher prices in later months, though the distribution would have been skewed towards the lower prices in Los Angeles, initially. In San Diego and Honolulu, an increase in dissemination would have caused the

distribution to become more peaked; while it would have led to a flatter distribution in Los Angeles.

These results suggest that, in Los Angeles, an increase in TV Share would have shifted the entire price distribution towards lower prices throughout the program. Moreover, the distribution would have become flatter. These two effects would have combined to low average price. This result is consistent with the price equation for Los Angeles which shows that the average price falls with an increase in dissemination.

In Honolulu, increased dissemination would have shifted the entire distribution to the left in the earlier periods, and would have skewed the distribution towards higher prices towards the end of the period. This result is different from that obtained from the price equation, where average prices fell after a six month lag, independent of the magnitude of TV Share.

The results for San Diego suggest that an increase in dissemination would shift the distribution towards higher prices initially. This effect is not necessarily inconsistent with the price equation. While the price equation showed that average prices fell after the start of the Vector program, the TV Share x 6 Months Time Trend term's coefficient is positive which implies that the more consumers exposed to the information, the higher the average price, all else the same. If the negative effect of dissemination in San Diego is correct, it is hard to understand how the Vector program has its desirable effects on the average price.

The inconsistencies in the price equation and distribution results are presumably due to the differing indexes used in the two studies, and the restricted time period used in the distribution study. By restricting the sample to just the period when the Vector program was in effect, the

distribution equations cannot capture the general effect of the Vector program which is independent of the degree of dissemination.

VIII.  Summary and Conclusions

Our empirical results suggest that the Vector program has increased competition and decreased prices, even though few consumers had access to the information.  The Vector information  substantially reduced average food prices (as measured by the BLS) in both San Diego and Los Angeles.  Though our estimates are less precise for Honolulu, apparently the Vector program reduced the average price there as well.

The Vector program increased concentration in Los Angeles and in San Diego  initially, and then reduced concentration.  Presumably, initially low-price stores' market shares rose and then, as other stores lowered their prices, shares became relatively equalized.  While the limited number of observations prevented us from statistically studying the effect in Honolulu, concentration fell there during each year the program was in effect.

We have limited confidence in our study of the effects of increased information dissemination on the distribution of prices across stores, because of the limited time period and Vector's unusual price indexes.  The disturbing implication of this study is that in some cities, increased dissemination of information may have adverse price effects.  In future studies, we hope to test this result using standard BLS expenditure weighted indexes rather than Vector's serving size weighted indexes.

The Vector information program differs from those previously studied in the use of cable television rather than newspapers to inform consumers, in

the length of time it has lasted, and in the more limited number of consumers exposed to the information. Apparently cable television is a practical means of informing consumers. Further, it appears that the substantial reduction in prices due to information found in earlier studies can be maintained over long periods. Indeed, our results suggest that it may be years before a Vector-like program lowers prices to their minimum levels. Collectively, our empirical studies suggest that a Vector-like program may be effective even (or possibly especially) when relatively few consumers are aware of the information.

In future research, we will examine the effect of Vector's relative price information on individual store's market shares. We also investigate the effect of the information program on items individually listed and those which are only included in the overall index. If these studies support the desirable effects of the Vector program reported here, we would suggest that government agencies should provide consumer information or should encourage private firms (such as Vector) to provide more information.

## References

G. A. Akerlof, "The Market for 'Lemons': Qualitative Uncertainty and the Market Mechanism," Quarterly Journal of Economics, August, 1970, 84: 488-500.

Robert D. Boynton, Joseph N. Uhl, Brian F. Blake, and Vicki A. McCracken, "An Analysis of the Impacts of Comparative Food Store Price Reporting on Price Structures and Consumer Behavior, Purdue University Agricultural Experiment Station Research Bulletin 968, August 1981.

Burgoyne, Inc., The National Study of Supermarket Shoppers, 1977, City Profile.

D. Grant Devine, "A Review of the Experimental Effects of Increased Price Information on the Performance of Canadian Retail Food Stores in the 1970's," Canadian Journal of Agricultural Economics, 1978, 26: 24-29.

D. Grant Devine and Bruce W. Marion, "The Influence of Consumer Price Information on Retail Pricing and Consumer Behavior," American Journal of Agricultural Economics, May, 1979: 228-237.

P. A. Diamond, "A Model of Price Adjustment," Journal of Economic Theory, June, 1971, 3: 156-68.

Robert T. Michael, "Variation across Households in the Rate of Inflation," Journal of Money, Credit and Banking, February, 1979, 11: 32-46.

Jeffrey M. Perloff and Steven C. Salop, "Imperfect Information, Product Differentiation, and Entry," University of California, Berkeley Department of Agricultural and Resource Economics Working Paper No. 154, 1981.

Scitovsky, "Ignorance as a Source of Oligopoly Power," <u>American Economic</u> <u>Review</u>, March, 1950, 40:  48-53.

G. Stigler, "The Economics of Information," <u>Journal of Political Economy</u>, June, 1961, 69:  213-25.