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Sales: Tests of Theories on Causality and Timing

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Abstract

Modern theories of sales make conflicting predictions about the temporal pattern of sales, which we test using grocery scanner data. We examine both frozen orange juice, which consumers can store, and refrigerated orange juice, which is more perishable, to determine what role-if any-durability plays in the pattern of sales. We start with a simple reduced-form probit analysis to examine the timing of sales and whether sales are determined nationally by manufacturers or locally by retailers. We then turn to a vector autoregressive analysis and conduct Granger tests of temporal ordering ("causality tests") to determine whether the sale of one brand is followed in a predictable way by the sale of another brand or its own later sales. Based on the VAR estimates, we simulate impulse responses to determine the magnitude of these time-series effects. In fact, none of the theories of sales fully describes sale patterns and price distributions. We find product durability makes little difference in sales patterns. We show that, contrary to all the existing theories, retailers rather than manufacturers determine sales. Despite sale patterns not being significantly different for national brands and private label brands, our formal Granger causality analysis shows that a sale of a national brand is more likely to "cause" sales of other products than is a sale of a private label product.

Sales: Tests of Theories

on Causality and Timing

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Abstract

Modern theories of sales make conflicting predictions about the temporal pattern of sales, which we test using grocery scanner data. We examine both frozen orange juice, which consumers can store, and refrigerated orange juice, which is more perishable, to determine what role—if any—durability plays in the pattern of sales. We start with a simple reduced-form probit analysis to examine the timing of sales and whether sales are determined nationally by manufacturers or locally by retailers. We then turn to a vector autoregressive analysis and conduct Granger tests of temporal ordering ("causality tests") to determine whether the sale of one brand is followed in a predictable way by the sale of another brand or its own later sales. Based on the VAR estimates, we simulate impulse responses to determine the magnitude of these time-series effects. In fact, none of the theories of sales fully describes sale patterns and price distributions. We find product durability makes little difference in sales patterns. We show that, contrary to all the existing theories, retailers rather than manufacturers determine sales. Despite sale patterns not being significantly different for national brands and private label brands, our formal Granger causality analysis shows that a sale of a national brand is more likely to "cause" sales of other products than is a sale of a private label product.

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Does a sale—a temporary price reduction—of one product lead to a similar sale for rival products? Is the observed pattern of sales consistent with the predictions of current theories of sales? Are sales determined by manufacturers or retailers? We answer these questions using price data for refrigerated and frozen orange juice products in US grocery stores.

Although many theories offer explanations for price changes over time, only a few are clearly labeled as theories of sales. These theories of sales make conflicting predictions about the temporal pattern of sales. We compare and test these theories using orange juice grocery-store scanner data. To our knowledge, this paper is the first empirical study that examines the roles of both retailers and manufacturers in determining patterns of sales. Moreover, we believe that this paper is the first to study the role of product durability in determining sales. We contrast the patterns of sales for frozen orange juice, which can be stored, to that of refrigerated orange juice, which is much more perishable, to determine what role—if any—durability plays in pricing patterns.

We begin by summarizing the various theories of sales in Section 1 and then derive testable hypotheses from them in Section 2. After briefly describing the grocery scanner data in Section 3, we discuss the empirical analyses. In Section 4, we present summary statistics, histograms, and correlations of prices and sales from which we conclude that no theory of sales fully describes sale patterns and price distributions. The correlation evidence indicates that retailers rather than manufacturers determine price patterns. We do not find any clear-cut differences in sales patterns between the more durable frozen orange juice and perishable refrigerated orange juice.

In Section 5, we examine the timing and causes of sales using two types of models. We start with a simple probit model of whether a sale occurs this period given the length of time since previous sales and other variables that are proxies for whether national manufacturers or local retailers determine prices. We then turn to a vector autocorrelation model to forecast a brand's price conditional on past prices of that brand and those of its rivals. We use Granger tests of temporal ordering ("causality test") to determine whether the sale of one brand is followed in a predictable way by the sale of another brand or its own later sales. We also simulate impulse responses to determine the magnitude of these time-series effects. Although the sale patterns do not differ significantly for national brands and private label brands, a formal Granger causality analysis shows that a sale of a national brand is more likely to cause sales of other products relative to a sale of a private label product. We summarize our results in the last section and draw conclusions.

1 Sales Theories

The various theories of intertemporal pricing make conflicting predictions about the timing of sales. In this section, we review several of the best known theories and use those theories to derive testable hypotheses.

Although many theories offer explanations for price changes over time, only a few are clearly labeled as theories of sales. One literature describes price discrimination over time with consumers varying in tastes or knowledge about prices (Salop 1977, Salop and Stiglitz 1982). In a related literature, firms price discriminate by inducing some consumers to buy and store extra units when prices are low (Conlisk, Gertsner, and Sobel 1984, Pesendorfer 2002, Sobel 1984). In another sales literature, firms use mixed strategies to set prices (Shilony 1977, Varian 1980, Lal 1990, and Lal and Villas-Boas 1998). Most of the models in these literatures assume that there are two (or more) types of consumers with varying search costs—for example, informed consumers with no cost of search and other consumers with relatively high costs of search.

Most of the price discrimination literature examines markets in which goods are homogeneous. Salop (1977) shows that a manufacturer may set different prices for a relatively undifferentiated product under several different brand names. Informed consumers who know the products are identical purchase the least expensive brand, while less-informed consumers may pay higher prices for other virtually-identical goods. Though his model is static, Salop notes that varying the location of the low prices over time might be a feasible dynamic strategy.

Salop and Stiglitz (1982) use a two-period model with storage to show that stores may use (unannounced) sales to induce apparently homogeneous consumers to purchase for future consumption. Customers who arrive at a low-price store buy extra units and store them for later consumption, while customers who buy at a high-price store only buy for their immediate needs. Thus, firms can successfully price discriminate by using unannounced sales. With identical firms and consumers, we may observe a two-price equilibrium where the low-price store makes more sales than a high-price store, but both stores have the same profit.

Conlisk, Gerstner, and Sobel (1984) show that price reductions for durable goods can be a means of price discriminating against consumers who are impatient and have relatively inelastic demands.[1] In their model, a monopoly uses a cyclical pricing strategy. Periodic sales are aimed at consumers with relatively low reservation prices, while periods of higher prices are aimed at consumers with higher reservation prices.

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[1] A somewhat related literature explains why prices fall over time—e.g., the intertemporal durable good price discrimination story of Stokey (1979, 1981). However, it does not explain why temporary sales are conducted.

Sobel (1984) extends the monopoly model in Conlisk, Gerstner, and Sobel (1984) to a fixed number of sellers that produce a homogeneous good. Consumers with different preferences for a homogeneous good enter the market in each period and leave when they make a purchase. Again, sellers vary their prices over time, charging relatively high prices most of the time, but occasionally cutting their prices to sell to a large group of customers with relatively low reservation prices. His model depends crucially on consumers having different rates of time preference that are correlated with the intensity of preferences. One interesting property of his model is that all stores may lower their price at the same time and to the same level. In both the Sobel and Conlisk, Grestner, and Sobel models, a smooth pattern of price adjustment is observed. In Sobel, the firms' prices are initially high and each firm sells to high-storage costs ("loyal") consumers. As time passes, when potentially a large number of low storage consumers ("shoppers") are in the market, it becomes profitable to decrease prices and to compete for those consumers. Then firm's prices rise again beginning a new cycle.

In Pesendorfer (2002), some customers consume one unit of the good every period and do not store the product, while others maintain an inventory that they consume if the prices are temporarily high. Consumers who store the good only purchase the product if price drops below a certain threshold. Pesendorfer finds similar pricing patterns to Sobel.[2]

Other models concentrate on mixed strategies of competing firms rather than price discrimination. Shilony (1977) and Varian (1980) present static models in which sellers use mixed strategies. For example, Varian demonstrates that oligopolists selling homogeneous

[2] In a dynamic oligopoly setting with alternating pricing decisions, Maskin and Tirole (1988) predict a long-run equilibrium (focal) price or Edgeworth price cycles that are similar to the price patterns in Sobel (1984) and Pesendorfer (2002).

goods may use a mixed strategy in which they set low ("sale") prices some of the time to attract customers who have low shopping costs. If the game is replicated independently over many periods, the mixed strategies produce price variation over time according to an explicit, continuous probability distribution. Firms cut prices solely to compete with rivals rather than to price discriminate. Because the price reductions are random, firms are unlikely to have sales at the same times, and prices should be neither correlated over time nor predictable (Villas-Boas, 1995). In contrast, in Green and Porter's (1984) dynamic oligopoly game with imperfect information, temporary price reductions by all firms are triggered by a price signal caused by fluctuations in demand or other unknown causes.

In the infinite-horizon model of Lal (1990), national brands alternate promotions to keep private labels from stealing those consumers who are willing to switch brands. In the perfect Nash equilibrium, two national firms implicitly collude to keep out a potential entrant.[3]

2 Hypotheses and Empirical Strategies

The theoretical models discussed in Section 1 have very different implications in terms of the patterns of prices we might actually observe in a market. We use these differences to formulate testable hypotheses and also consider several hypotheses based on popular beliefs (newspaper and trade articles). To organize our discussion of the tests and results, we divide the hypotheses into groups based on the empirical evidence we use to study them. Our first set of hypotheses can be examined using summary statistics in Section 4. The others require formal models discussed in Section 5.

[3] Agrawal (1996) adds a retailer pricing decision to the manufacturing pricing decision. Lal and Villas-Boas (1998) derive a model of price promotions in the presence of multiple retailers.

We start by examining three hypotheses that can be addressed using summary statistics and correlation analysis. First, national brands have sales more frequently than do private labels. Lal provides a possible explanation for such a result—in his model, national brands hold sales to drive out fringe firms. Moreover, many models and descriptive studies contend that private labels are less able to cut price during a sale because they are priced closer to marginal cost than are national brands.

Second, the existing sales literature presents conflicting predictions about the distribution of prices over time. We use our data set to examine three price distribution-related hypotheses. Some models suggest an explicit distribution of prices. The game theoretic models of Shilony (1977), Varian (1980), and Lal (1990) provide closed form, continuous frequency of prices (mixed strategies). In theories based on durable goods or Sobel (1984) and Pesendorfer (2002), prices fall smoothly over time and then jump to a high level, so we should see a smooth histogram with possibly a mass point. Lal (1990) predicts alternating sales by the major brands and not by private labels, so the distribution of prices for a major brand might have two or more mass points and the private label's distribution should have one mass point. We also examine price histograms for individual stores to see if a clear pattern emerges by brand or by more- and less-storable types of orange juice.[4] For example, if the mixed-strategy story is correct, then prices should not remain constant over long periods of time. Villas-Boas (1995) tests and rejects Varian's (1980) closed-form distribution hypothesis.

[4] According to the various theories, if consumers differ across stores in terms of their elasticities of demand, ability to store goods (e.g., capacity of their freezer), or costs of search, we might see different price patterns across stores with different mixes of consumers. We looked at store-level data to see if one model's predictions dominated for certain types of stores (e.g., those with low-income consumers) and did not see a clear pattern.

Third, if sales occur only when brand-name manufacturers provide sales incentives (temporary reductions in the wholesale price and other inducements) to many stores at the same time, the timing of sales will be correlated across stores. All the major sales theories presume that manufacturers determine pricing.[5] By examining correlations and using formal models, we consider whether sales are determined nationally by the manufacturer, by city through some form of competition, or by chain.

Next, we use formal models to investigate four more hypotheses about the timing of sales. We investigate whether sales in certain products cause sales in other products and to what degree being a major brand, being in the same market, or being in the same retail chain is important in explaining causality of sales.

Fourth, according to Pesendorfer (2002), the length of time since the last sale should determine when the next sale occurs.[6] That is, there is a systematic pattern in timing. We test this hypothesis using a probit model.

Fifth, several of the models make testable predictions about the timing of sales across stores or brands. According to Sobel (1984) and Green and Porter (1984), stores may lower prices at the same time. In Shilony (1977), and Varian (1980), stores will almost never hold simultaneous sales. Lal (1990) predicts alternating sales by the major brands. We examine these hypotheses using both probit and vector autoregressive (VAR) models.

Sixth, given different predictions by these theories that assume that the good is storable and those that consider only perishable goods, one might expect that the temporal price patterns

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[5] Green and Porter (1984) provide an alternative explanation—trigger-price collusive behavior—for why stores in a market may lower or raise prices at the same time. This explanation might be relevant for a single city, but not for the country as a whole.

[6] See also Hendel and Nevo (2006) on consumer demand with storable goods.

to vary with the durability of the product. If manufacturers determine sales and price-sensitive consumers prefer name-brand products, manufacturers may hold periodic but infrequent sales to "sweep" these consumers out of the market by getting them to buy durable, frozen orange juice and store it rather than buy the house brand. Such a strategy is not attractive if consumers cannot store the good, as with refrigerated orange juice. In Varian's (1980) model of homogenous, nonstorable goods, the timing of sales is random. In contrast, in Sobel (1984) and Pesendorfer (2002) durable good theories, prices will change predictably; prices will fall smoothly over time and then increase by a large discrete amount to start the cycle again. Some durable-good models predict that the probability of a sale should increase given the time since last promotion (Pesendorfer 2002). Consequently, we compare temporal price patterns for frozen orange juice, which can be stored for many weeks, to those for refrigerated orange juice, which cannot be stored for long periods of time. We estimate probit and VAR models separately for durable and nondurable goods and compare the results.

Seventh, because stores receive a larger markup for their private label products, they may decide not to have private label sales at all or to coordinate them with brand-name sales. Presumably, if manufacturers are determining when sales occur, private label sales are unlikely to affect sales of brand-name products; however, sales of brand-name products may have an effect on other brand-name products. We address these hypotheses using VAR models and impulse simulations based on the VAR estimates.

3 Data

We test these hypotheses using a three-year panel of weekly price observations for refrigerated and frozen orange juice from 174 grocery stores in 24 cities from Information

Resources Incorporated (IRI). We focus on the last two years of this data set, 104 observations for 1998 and 1999, reserving observations from the first year of data, 1997, for lags.

For some stores, we do not have complete price series for all products in each week either because the store did not carry that product that week or due to data errors. Consequently, we restrict our sample to only those stores that have complete price series for all key orange juice products. The resulting refrigerated orange juice data sample has prices from 22 stores in 13 different cities.[7] The frozen juice prices data set includes 10 stores in Cedar Rapids IA, Eau Claire WI, and Minneapolis MN. In the refrigerated orange juice sample, some, but not all of the stores, are owned by one of seven national chains. In the frozen sample, two chains each own multiple stores.

We restrict our attention to the major national brands and the stores' private label products. In the last year of our sample, 1999, the three leading national brands of refrigerated orange juice were Tropicana, with 22.2 percent market share by sales, Minute Maid, with 16.3 percent market share, and Florida Natural, with 5.1 percent market share (www.beverage-digest.com/editorial/991105.html). We restrict our analysis to the leading product for each brand-name: Tropicana Premium Orange Juice, No Pulp; Minute Maid Premium Original Calcium Orange Juice, Low Pulp; Florida Natural Premium Orange Juice; and each store's best-selling private label product. Among frozen concentrates, Minute Maid is the dominant brand, accounting for 40 percent of the market share. We track Minute Maid, Old Orchard, and each store's best-selling frozen private label product in our analysis.

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[7] Atlanta, GA; Boston, MA; Chicago, IL; Eau Claire, WI; Grand Junction, CO; Los Angeles, CA; Midland, TX; Minneapolis, MN; Pittsfield, MA; San Francisco, CA; Seattle, WA; St. Louis, MO; and Tampa, FL.

For each observation, the IRI data set contains price, store identifier, and market (city) identifier. We augmented this data set by adding the corresponding monthly packing-house-door price for juice orange in dollars per box from the USDA-NASS Agricultural Prices Monthly (usda.mannlib.cornell.edu/reports/nassr/price/pap-bb) and the Consumer Price Index (CPI).

4 Summary Statistics

Prices for both refrigerated and frozen orange juice vary substantially over time, even though they exhibit little trend over time. Table 1 shows the mean, standard deviation, minimum price, and maximum price for various types of orange juice. The refrigerated orange juice price is expressed as dollars per 64 ounce carton, while the frozen product price corresponds to 12 fluid ounce cans of frozen concentrate. For refrigerated juice, these summary statistics were calculated over all 22 stores and all 104 weeks for a total of 2,288 (= 22 × 104) observations. The "minimum price" rows report the minimum price *by week* as calculated *across* 22 stores for refrigerated products and across 10 stores for frozen products. The standard deviation is for these minimum prices across the 104 weeks.

The highest price by brand was often two or three times the lowest price.[8] The coefficients of variation of the minimum prices are comparable across the refrigerated and frozen samples.

Most of the variation in price over time for a given product within a store is due to temporary reductions (or, in a few cases, increases) rather than due to a trend. Table 2 reports sale-related summary statistics for several different definitions of a sale price. In the first set of

[8] Variations in prices *within* single weeks (not shown) were also substantial. On average, within-week standard deviations ranged from 45¢ for refrigerated Tropicana prices to $1.07 for private label products prices. For frozen products, average within-week standard deviations in prices ranged from 15¢ for private label juice to 19¢ for Minute Maid.

columns, a store has a product "on sale" if its weekly price is at least 25 percent below the mode price (across all weeks in the two year period) for that product in that store. When "on sale" is defined as a price that is at least 35 percent below the mode prices, as in the second set of columns in Table 2, we see that the products are on sale much less frequently. When a sale price was defined as any price more than 50 percent below the mode, very few of the products are "on sale"—in fact, the price of frozen Minute Maid is never more than 50 percent below the mode store price. By any of these definitions, there are a few stores that never have sales and many that have sales that last no more than two weeks per year.

Contrary to common belief and our first hypothesis, national brands do not necessarily go on sale more frequently than do private label products. Using the 25 percent criterion for a sale, refrigerated Florida Natural is on sale in approximately 5.87 percent of the weeks in the sample. Tropicana and the private label products are on sale only slightly less frequently: 5.85 and 5.66 percent of the weeks, respectively. Minute Maid is on sale only 3.46 percent of the time.

Results are similar for the frozen products. Minute Maid is on sale relatively infrequently (4.8 percent of weeks), while private label frozen orange juice is on sale more than 10 percent of the time. Thus, we do not find a distinction between more and less durable products as one might expect given theories such as those of Sobel (1984) and Conlisk, Gerstner, Sobel (1984).

Histograms of Prices

To examine our second hypothesis concerning the distribution of prices of a given product over time, we examined each store's histogram of 1998 prices. Recall that in Shilony (1977) and Varian (1980) prices are derived from firms' mixed strategies. In contrast, prices fall smoothly and then increase in dramatic jumps in hypotheses based on durable goods. A third possibility, Lal (1990), is that major brands have alternating sales. In fact, these histograms illustrate that no single model of sales describes pricing patterns across all stores.

To illustrate the various patterns, we display histograms from two typical stores. The top half of Figure 1 shows the price distribution for each refrigerated brand in a typical store in Grand Junction, Colorado. Tropicana's price distribution may be (loosely) described as uniform, as several prices occur with roughly equal frequency in the dataset. The distributions are virtually unimodal for Florida Natural and Minute Maid, while almost all of the weight is in two adjacent prices (essentially a single mass point rather than a bimodal distribution) for the private label. The bottom half of Figure 1 shows three distributions for frozen orange juice in another typical store in Cedar Rapids, Iowa. Minute Maid has a nearly unimodal distribution, the private label is basically bimodal, and Old Orchard has two adjacent dominant prices.

For refrigerated orange juice, there are 4 brands in 22 stores, or 88 price distributions. Of these 88 price distributions, 26 had a bimodal pattern, 31 had one price virtually every week, 20 had a strong central tendency (roughly normal distribution), and 4 appear to be uniformly distributed (several prices occurred with virtually identical frequencies). For the 30 (3 brands in 10 stores) frozen orange juice price distributions, 5 had a clear bimodal pattern, 19 had essentially one price all the time, 3 exhibited a strong central tendency, and 2 had a relatively uniform distribution of prices.

Less than one-third of the refrigerated and one-sixth of the frozen price distributions suggest that stores pursue mixed strategies in pricing. We find little evidence to support the mixed strategy hypothesis that price distributions would be continuous and lack mass points. There is also only weak evidence supporting the hypothesis that price fall smoothly and then jump. Less than half of the refrigerated product histograms show a single mass point, while two-thirds of the frozen product price histograms were unimodal. Fewer than a third of the stores for refrigerated orange juice and a sixth for frozen orange juice exhibit the bimodal pattern (two, nonadjacent peaks) that one would expect if sales were alternated with a regular price. This evidence is inconsistent with the hypothesis that stores alternate sales of major brands.

Thus, the price histograms provide descriptive evidence that no single model of sales describes pricing patterns across all stores. Moreover, a comparison of the histograms for refrigerated and frozen orange juice indicates that sale price patterns do not vary systematically by product storability.

Correlations

Are sales determined by manufacturers or retailers? Our third hypothesis suggests that the timing of sales is correlated, and we refine this conjecture to ask whether sales are determined by individual stores, by chains or by manufacturers on a national level. To answer these questions, we calculate the correlations between prices at the national, market, and chain levels in Table 3. These summary statistics were calculated by averaging the correlations of prices for a given product at different stores, grouping the stores either by chain or location. The national level is the "broadest" statistic, capturing the correlations between prices of a given product across all stores. The market level statistics groups stores by city, and the chain statistics summarizes correlations across stores belonging to the same chain.[9]

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[9] Suppose there are four stores A, B, C, and D. Stores A, B, and D are located in the same market, and B and D belong to the same chain. The national mean correlation for Tropicana would be the average of correlation coefficients for Tropicana prices in A and B, A and C, A and D, B and C, B and D, and C and D. The market statistics would be calculated from the correlation coefficients for Tropicana prices in A and B, A and D, and B and D. The chain correlation average would the correlation coefficient between Tropicana prices in B and D.

There is surprisingly little price correlation at the national level, with the correlation coefficients averaging between 0.30 and 0.45 for the various brands of refrigerated orange juice. The correlation coefficients for frozen orange juice are even lower. Indeed, the correlation across all the refrigerated private label products at the national level is not much lower than the correlation coefficient for the national brands. For frozen products, the private label and Minute Maid have similar correlations, while Old Orchard has a higher coefficient. Thus, it seems unlikely that manufacturers are determining when sales occur at a national level.

The average market-level correlation for both refrigerated and frozen orange juice is substantially greater than the national level correlation. The correlations are significantly higher at the chain level than at the city level for refrigerated juice, whereas the correlations are roughly equal for frozen juice. For refrigerated juice, two of several chains had prices that were perfectly correlated across the stores of the chain. For the remaining five chains, the correlations across the stores of the chains were above 0.5 for national brands. Thus, it seems that refrigerated prices are set by the chains with some local variation while frozen juice prices are set at either the city or chain level. National manufacturers do not determine the prices nationally for refrigerated or frozen juice.

5 Empirical Analysis of Timing and Causality

We test the hypotheses concerning sale timing and causality, using a variety of models. To begin, we examine whether prices exhibit trends. Failing to find significant trends, we concentrate on the timing and causality of sales. To provide a benchmark and examine our fourth hypothesis, we estimate a probit model, similar to the one presented by Pesendorfer (2002), that attempts to predict sales based on past sales. Then, to examine our last three hypotheses, we turn to a vector autocorrelation model, where we consider both price and the log price as the variable of interest. Because deflating prices by the CPI makes no appreciable difference in this two-year period, we report all statistics using nominal prices.

Trends and Unit Roots of Price Data

Using price in an augmented Dickey-Fuller test, we reject the unit root hypothesis at the 0.05 percent level in 68 of 88 brand-store combinations: 19 for Tropicana, 18 for Florida Natural, 15 for Minute Maid, and 16 for the private label. Using the log of price, we get similar results, rejecting the unit root in 66 of 88 brand-store combinations: 19 for Tropicana, 18 for Florida Natural, 15 for Minute Maid, and 14 for the private label.

Using price, we reject the unit root hypothesis at the 0.05 percent level in 68 of 88 brand-store combinations: 19 for Tropicana, 18 for Florida Natural, 15 for Minute Maid, and 16 for the private label. Using the log of price, we get similar results, rejecting the unit root in 66 of 88 brand-store combinations: 19 for Tropicana, 18 for Florida Natural, 15 for Minute Maid, and 14 for the private label.

Testing for a price trend (where the null hypothesis is a random walk) by regressing price on a constant and a time trend, we fail to reject the null hypothesis of no trend in 34 of 88 cases: 6 for Tropicana, 9 for Florida Natural, 12 for Minute Maid, and 7 for the private label. The summary of results using the log of price is similar.

The estimated trend coefficients are very small (regardless of whether they are or are not statistically significantly different from zero). On average, trend coefficients with price are less than 0.003 (0.3¢ per week): 0.0018 for Tropicana, 0.0022 for Florida Natural, 0.0023 for Minute Maid, and 0.0027 for the private label. On average, the trend coefficients with log prices are 0.0006 for Tropicana and 0.0009 for the other products. We conclude that there is no economically or statistically meaningful trend in these data and that the variation within the price series must be due to something other than a steady change in price.

Confident that the data does not exhibit strong trends, we use more formal econometric tool to test our remaining three hypotheses. In the remainder of Section 5, we discuss the results from the probit regressions, vector autoregressive regressions, Granger tests and impulse-response analysis.

Probit Analyses

Sales may cause sales. That is, sale pricing of a certain product may be due to sale of another product in the same store or chain, or across stores, chains and cities. To determine the probability that a sale of one brand "causes" a sale in another brand within a store, we estimate a probit model for each product where the dependent variable equals one if the product in a store in a given week is on sale. Again, we define a sale as occurring when a store sets a price that is at least 25 percent below the mode price in that store.[10]

Our chief explanatory variables are the number of weeks since the last sale of this product and the rival products in this store and the minimum number of weeks since a sale in this market (city) for each product. The latter measures are designed to capture the effect of incentives provided by the manufacturer that affect all stores within a city. Our results are virtually the same if we replace these city-level measures with the minimum number of weeks since the last sale in the entire sample for each product.

We also consider two types of dummy variables in our various specifications. Weekly dummies allow for the possibility of national-level pricing, nationwide promotional campaigns,

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[10] We obtain virtually identical results when we use the 35 percent threshold. The 50 percent definition of a sale results in too few sales for this analysis to be enlightening.

or seasonality in the cost of oranges or other critical inputs. Store dummies capture systematic differences in the use of sales across stores. We consider three specifications where we include only the weekly dummies, only store dummies, or both.

When we examine only refrigerated products and include both weekly and store dummy variables, none of the dummy variables was statistically significantly different from zero. However, in the frozen product regressions, some dummies were statistically significantly different from zero.

In regressions that include only the weekly dummies, none of these dummies is statistically significantly different from zero for refrigerated orange juice. Thus, we conclude that no time dependent, national phenomenon influences refrigerated orange juice prices. For the frozen product, a few weekly dummies were statistically significant for Minute Maid, suggesting that Minute Maid may engage in national promotional activities in a few weeks of the year. When only store indicators were included in the regressions, the dummies were statistically significant only in the refrigerated and frozen Minute Maid regressions.

Tables 4 and 5 report the probit coefficients and asymptotic standard errors for refrigerated and frozen products, respectively, where both sets of dummies variables are included. If the coefficients in the regression other than the constant term were zero, then sales are IID events, and this model would provide no useful prediction of sales. In fact, the likelihood-ratio (LR) test for this hypothesis is rejected in all cases.

This model does not provide the type of results one might expect. In both the refrigerated and frozen orange juice probit regressions, very few of the coefficients for weeks since the last sale in the own store are statistically significantly different from zero: 4 out of 16 for the refrigerated sample (2 were for the same given product) and 1 out of 9 for the frozen (and it was not for the same given product). All of the statistically significant coefficients are negative. Thus, either previous sales have no effect on current sales or, perversely, the longer it has been since a sale in a store, the less likely it is that a sale will occur this week. Of course, if a store rarely held sales in the past, it may be relatively unlikely to hold sales now.

The probit regressions also include a variable representing the number of weeks since a given product was on sale in any store in the given market. For the minimum number of weeks since the last sale in the market, only 5 out of 16 coefficients are statistically significant for the refrigerated sample, and only 2 out of 9 are significant for the frozen sample. In the refrigerated product regressions, three of the five statistically significant coefficients are positive and the rest are negative. For the frozen sample, one is positive and one is negative. In short, most coefficients are statistically insignificant, and no obvious sign pattern emerges for the statistically significant coefficients.

Pesendorfer (2002) estimates a similar model for ketchup. His results for ketchup are very different from our results for orange juice. We are fairly certain that our results do not differ from Pesendorfer's because of differences in our models, as we have also tried to replicate his specification.[11] However, our results may differ from Pesendorfer's because of the differences in the types of products we study.

Pesendorfer reports positive coefficients for the variables representing time since the last sale for both a store and the market. Thus, he concludes that there is a systematic pattern of sales

[11] Pesendorfer (2002) uses time trends and squared time trends instead of our weekly fixed effects. He also includes the square of the minimum number of weeks since last sale. We replicated this specification with our data, but did not get a significant coefficient on the squared term of weeks since last sale. Unlike Pesendorfer, we use levels rather than logs of the time variables. With logs, none of the Probit estimates achieve statistical significance.

that is inconsistent with the lack of a pattern predicted by Varian's mixed strategy story. Our results do not support Pesendorfer's conclusion. We find a very mixed pattern where past sales with a store or a market may encourage, inhibit, or have no effect on sales.

Granger Tests of Temporal Ordering

In the previous subsection we asked: Do the prices of one brand "cause" changes in the prices of another brand? That is, does the sale of one brand "cause" the sale of another? While the probit analysis provided some insight into the "causality" of sales, we also investigate with "Granger tests of temporal ordering." Following the standard but inaccurate terminology, we refer to these as Granger causality tests. Table 6 summarizes our Granger causality tests. We say that Brand A "Granger-causes" Brand B's price if we reject the hypothesis (at the 5 percent level) that the VAR (lagged price) coefficients for Brand A in the equation for Brand B's price are collectively zero using a likelihood-ratio test.

The first row of Table 6 shows that Tropicana's refrigerated orange juice price Granger-causes the Florida Natural price in 64 percent of the stores. The refrigerated private label price Granger-causes the brand prices 27 percent to 32 percent of the time, while the prices of the national brands Granger-cause the prices of the other brands and private label between 36 percent and 64 percent of the time. Tropicana—the brand with the largest market share—has the largest effect on the prices of rival products, followed by Florida Natural, and Minute Maid.

For frozen orange juice brands, Minute Maid's price Granger-causes the price of Old Orchard and the private label 60 percent of the time, the Old Orchard price Granger-causes Minute Maid's price 60 percent of the time but private label's price only 30 percent, and the private label price Granger-causes Minute Maid's price 30 percent and Old Orchard's price 20 percent of the time. Thus, for both refrigerated and frozen products, sales of major national brands are more likely to "cause" later sales by other brands than are sales of private label products.

Vector Autoregression Analyses

In a previous subsection, we used probit models to forecast the probability of a sale given the timing of past sales. By recasting the problem as a vector autoregressive process, we can forecast price conditional on past prices of a given brand and those of its rivals. Given estimates of a vector autoregressive model, we test of the hypotheses that past prices of a given brand and its rivals "cause" the present price of a brand. We then use these estimates to forecast product prices taking into account of all the feedback effects between brands. For instance, our vector autoregressive model—but not our probit model—can detect the pattern that brand A has a sale that "causes" brand B to have a sale which in turn causes brand A to have a sale.

We estimate vector autoregressive (VAR) models for both prices and the log of prices of each brand within a store, separately for refrigerated and for frozen products.[12] Because the results are qualitatively very similar, we discuss only the log price results.

For each store, we estimate two systems of VARs equations. First, we use the prices of the other brands within a given store to estimate a single product's price series. Second, we use the prices of the other brands within a store and the minimum of the prices of the other brands within that market. In both systems, we also include quarterly dummy variables, packing-house-door price for juice oranges, and the CPI (these variables were not lagged).

For refrigerated orange juice, we estimate four equations, one for the price of each of the

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[12] We do not difference. One might think that if a series has a unit root, it is better to first difference the variable before using it in the VAR. However, taking first differences does not improve prediction if a series has a unit root, and differencing decreases prediction accuracy in the absence of a unit root.

four brands. Schwarz Information Criterion (SIC) and the Akaike Information Criterion (AIC) procedures were used to establish the appropriate lag length. While AIC results failed to indicate appropriate lag length, the SIC procedure suggested eight, eight, seven and six week lag lengths for Tropicana, Florida Natural, Minute Maid and the private label juice, respectively.[13] We use an eight-week lag in all of these regressions. As an experiment, we also tried 10- and 12-week lags and found that our results were virtually unchanged.

Using LR tests, we reject the null hypothesis that all slope coefficients (i.e. all coefficients except the constants) are equal to zero in 83 of 88 regressions for refrigerated prices and for 28 of 30 cases for frozen prices. Thus, there are only a few stores for which the prices are best explained as random variation about a constant term. The average R^2 measures for the refrigerated juice VARs are 0.70 (standard deviation is 0.17, minimum is 0.36, and maximum is 0.96) for Tropicana, 0.71 (0.20, 0.31, 0.99) for Florida Natural, 0.79(0.15, 0.50, 0.96) for Minute Maid, and 0.72 (0.21, 0.41, 0.98) for the private labels. The corresponding average R^2 measures for frozen products are 0.49 (0.12, 0.23, 0.64) for Minute Maid, 0.65 (0.14, 0.46, 0.80) for Old Orchard, and 0.54 (0.18, 0.29, 0.85) for the private labels.

Impulse Response Functions

While the bivariate Granger-causality tests above provide a statistical test of whether one brand's price is useful in predicting another brand's price, they do not show the degree of the response. Consequently, we turn to an impulse-response analysis to show how much a brand's price changes over time as a function of a change in the price of either itself or another brand. We compute impulse-responses for each VAR and construct graphical representations of the impulse and responses to show how a set of prices reacts over time to a price shock. The

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[13] For a few series, the AIC suggests more than 30 lags, which is infeasible with our dataset.

response takes account of changes throughout the system. For example, if the Tropicana price "changes" the Minute Maid price and the Minute Maid price changes the private label price, but Tropicana does not directly change the private label price, then these indirect price effects will appear in the impulse-response but not in the bivariate Granger tests. Because our VAR estimation uses the log of product prices, impulses and responses can be interpreted as percentage changes in price.

Figure 2 provides a sample of the impulse responses for frozen orange juice in a single store. It shows the response of prices of frozen Minute Maid, Old Orchard, and a private label product to a one-standard-deviation[14] upward shock to the Minute Maid price. The figure illustrates that a Minute Maid price increase of 7 percent leads to a price increase of approximately 3 percent three weeks later in the private label. The maximum price response from Old Orchard is an increase of less than half of 1 percent.

The impulse responses for frozen and refrigerated orange juice prices are summarized in Table 7. We test whether the effects are statistically significantly different from zero using asymptotic standard errors.

The table shows the number of stores that experienced at least one statistically significant (α = 5 percent level) price responses exceeding 50 percent of the impulse within 10 weeks of the shock. For each product, store, and week, we test the null hypothesis that a response equals zero (i.e. no response using a 5 percent criterion). When the test led to rejection of the null and the response was greater than 50 percent of the impulse value, we included the event in our count. For example, if the price of Tropicana in a given store in given week changed by more than 6

[14] One standard deviation of the two-year log price series for a given product in a given store.

percent after a 12 percent increase in the price of Minute Maid in that store, then we would count that impulse-response in the table.

In general, the price responses between brands within a single store are weak. The strongest effects are own-brand price effects. By examining the 88 impulse response figures, we find that Florida Natural and Minute Maid, in 10 and 13 stores respectively, have a pattern where a decrease in a product's own-price leads first to an own-price increase and then a decrease.

The strongest effect on another refrigerated brand was the effect of the price of refrigerated Minute Maid on the private label price. A Minute Maid price decrease led to a price decrease of at least half the magnitude in the private label product in 41 percent of the stores. Price changes for Tropicana, the refrigerated orange juice market leader, have their greatest effect on private label (27 percent of stores). The private label has little effect (at most, in 14 percent of stores) on any of the name brands.

For frozen orange juices, again the largest effect is an own effect. An Old Orchard sale results in another sale of at least half the first sales magnitude within 10 weeks in 30 percent of the stores. The largest cross effect is that of the market leader, Minute Maid, on both Old Orchard and the private label, where 2 stores showed a price response of 50 percent of the impulse. To summarize, for both frozen and refrigerated orange juice, a sale of one brand of orange juice triggers a price response by other brands of at least half the magnitude of the original sale in fewer than half the cases.

6 Conclusions

Based on a variety of time-series analyses, we conclude that no one theory of sales fully describes pricing practices for either refrigerated or frozen orange juice. However, we did learn several things:

First, contrary to popular belief, sales are not more frequent for national brands than for house brands. Indeed, for frozen concentrate, private labels are substantially more likely to be on sale than is Minute Maid, the dominant national product.

Second, based on correlations and other evidence, sales of orange juice brands are determined by stores or chains rather than by manufacturers. This result may explain why the leading theories of sales, which presume that manufacturers determine pricing, do not predict sales patterns for orange juice very well. This result also has implications for modeling and estimating price cost margins along the distribution chain. It highlights the role retailers play in determining price variations—retailers are not passive (see Chevalier et al. 2003 for similar findings).

Third, the various sales theories make conflicting predictions about the distribution of prices, none of which holds universally. The frequency of sales, the depth of the sale, and the resulting price distribution vary substantially across stores. We see histograms with smooth, quadratic shapes (as with the mixed strategies in Varian 1980), distributions with one or two mass points (Lal 1990), and other patterns. That is, we see a variety of pricing patterns across the majority of stores.

Fourth, we fail to confirm Pesendorfer's (2002) prediction that the probability of a sale depends on the time since the last sale of various brands. We do not find such a clear pattern of timing.

Fifth, stores do not time sales as predicted by any of the models. Given mixed strategy equilibria, we would not expect to see any systematic patterns, but some do indeed occur. We find no evidence that name-brand products go on sale at the same time (Sobel 1984, Green and Porter 1984), systematically alternate sales (Lal 1990), or slowly reduce prices for durable goods and then increase price substantially (Sobel 1984, Maskin and Tirole 1988, and Pesendorfer 2002). Most of the variation in orange juice prices over time is due to temporary price reductions, which sometimes exceeded 50 percent, rather than to a time trend or patterns of smooth adjustment.

Sixth, we fail to see a clear difference between refrigerated and frozen pricing patterns. Thus, we fail to confirm that durable goods (frozen orange juice) should have qualitatively different pricing pattern than less-durable goods (refrigerated orange juice). However, we do find some systematic quantitative differences.

Seventh, a Granger causality (temporal ordering) test indicates that a sale of a major national brand is more likely to "cause" later sales of other brands than is a sale of a private label product—one of the few hypotheses that we confirm. A sale of a major national brand "causes" sales of other brands in at least half the stores for only one-quarter of the other refrigerated brands and half the frozen brands.

An impulse response analysis shows substantial differences across brands in the size of the response of rival brands to a sale. A past sale by a brand has a much larger effect than a past sale of a rival brand on its own later sales. Compared to other refrigerated or frozen orange juice brands, Minute Maid sales result in more large-price responses in other brands' prices. Nonetheless, for both frozen and refrigerated orange juice, a sale of one brand of orange juice triggers a price response of other brands of at least half the magnitude of the original sale in fewer than half of the cases.

References

Agrawal, D., 1996. "Effect of Brand Loyalty on Advertising and Trade Promotions: A Game Theoretic Analysis with Empirical Evidence," *Marketing Science*, 15, N. 1.

Chevalier, J.A., A. K. Kashyap and P.E. Rossi, 2003. "Why don't Prices Rise During Periods of Peak Demand? Evidence from Scanner Data," American Economic Review, 93 (1): 15-37 .

Conlisk, J., E. Gerstner, and J. Sobel. 1984. "Cyclic Pricing by a Durable Goods Monopolist," *Quarterly Journal of Economics*, 99:489-505.

Green, E. and R. Porter, 1984. "Non-cooperative Collusion under Imperfect Price Information," *Econometrica*, 52: 87-100.

Hendel, I., and A. Nevo, "Sales and Consumer Inventory," 2002, NBER Working Paper No. w9048.

Lal, R. 1990. "Price Promotions: Limiting Competitive Encroachment," *Marketing Science*, 9: 247-262.

Lal, R. and J. M. Villas-Boas, 1998. "Price Promotions and Trade Deals with Multiple Retailers," *Management Science*, 44, N. 7: 935-949.

Maskin, E. and J. Tirole, 1988. "A Theory of Dynamic Oligopoly II: Price Competition, Kinked Demand and Edgeworth Cycles," *Econometrica*, 56, N. 3: 571-599.

Hendel, I. and A. Nevo, 2006. "Measuring the Implications of Sales and Consumer Inventory Behavior," *Econometrica*, 74, N. 6: 1637-73

Pesendorfer, M. 2002. "Retail Sales: A Study of Pricing Behavior in Supermarkets," *Journal of Business*, 75: 33-66.

Salop, S. C. 1977. "The Noisy Monopolist," *Review of Economic Studies*, 44:393-406.

Salop, S. C., and J. E. Stiglitz. 1982. "The Theory of Sales: A Simple Model of Equilibrium Price Dispersion with Identical Agents," *American Economic Review*, 72:1121-1130.

Shilony, Y. 1977. "Mixed Pricing in Oligopoly," *Journal of Economic Theory*, 14: 373-388.

Sobel, J. 1984. "The Timing of Sales," *Review of Economic Studies*, 51: 353-368.

Stokey, N. L. 1979. "Intertemporal Price Discrimination," *Quarterly Journal of Economics*, XCIII:355-71.

Stokey, N. L. 1981. "Rational Expectations and Durable Goods Pricing," *Bell Journal of Economics and Management Science*, 12:112-28.

Varian, H. 1980. "A Model of Sales," *American Economic Review*, 70: 651-659.

Villas-Boas, J. M., 1995. "Models of Competitive Price Promotions: Some Empirical Evidence from the Coffee and Saltine Crackers Markets," *Journal of Economics and Management Strategy,* 4: 85-107.

Table 1
Orange Juice Price Summary Statistics

	Mean	*SD*	*Min*	*Max*
Refrigerated Orange Juice				
(22 store; 13 cities; 7 chains)				
Price ($/64 fl oz. carton)				
Tropicana	3.04	0.49	1.68	3.99
Florida Natural	2.97	0.52	1.06	3.99
Minute Maid	2.90	0.54	1.50	3.99
Private label	2.55	1.07	0.50	4.99
Minimum price across stores in a given week				
Tropicana	2.15	0.29	1.68	2.69
Florida Natural	2.02	0.57	1.06	3.49
Minute Maid	2.08	0.44	1.50	2.99
Private label	0.85	0.10	0.50	0.99
Frozen Concentrated Orange Juice				
(10 stores; 3 cities; 2 chains)				
Price ($/12 fl oz. can)				
Minute Maid	1.56	0.22	0.88	1.77
Old Orchard	1.17	0.20	0.50	1.54
Private label	1.02	0.17	0.50	1.31
Minimum price across stores in a given week				
Minute Maid	1.19	0.17	0.88	1.51
Old Orchard	0.85	0.14	0.50	1.10
Private label	0.73	0.10	0.50	0.92

Table 2
Orange Juice Sales Summary Statistics
(Percent of weeks on sale by store)

	25% sale				35% sale		50% sale	
	Mean	*SD*	*Min*	*Max*	*Mean*	*SD*	*Mean*	*SD*
Refrigerated Orange Juice								
Tropicana	5.85	7.85	0	39.4	0.97	1.81	0.06	0.32
Florida Natural	5.87	7.82	0	29.8	1.83	3.02	0.55	1.30
Minute Maid	3.46	6.31	0	28.9	1.45	3.83	0.06	0.24
Private Label	5.66	7.87	0	40.4	3.92	7.05	1.38	3.49
Frozen Orange Juice								
Minute Maid	4.8	3.77	0	13.5	3.18	3.07	0	0
Old Orchard	5.39	9.9	0	49	3.78	8.21	0.10	0.29
Private label	10.55	8.14	0	30.8	4.53	5.85	0.20	0.59

Note: A "25% sale" occurs if a store's price drops by at least 75 percent below the store's mode price. A "35% sale" occurs if a store's price drops by at least 65 percent below the store's mode price. A "50% sale" occurs if a store's price drops by at least 50 percent below the store's mode price.

Table 3

Refrigerated Orange Juice Price Correlations at the National, Market, and Chain Levels

	Mean	*SD*	*Min*	*Max*
Refrigerated Orange Juice				
National Level				
Tropicana	0.33	0.22	0.00	1.00
Florida Natural	0.34	0.23	0.00	0.98
Minute Maid	0.42	0.22	0.00	0.92
Private Label	0.30	0.23	0.00	0.86
Market Level				
Tropicana	0.63	0.34	0.11	1.00
Florida Natural	0.61	0.34	0.05	1.00
Minute Maid	0.64	0.33	0.05	1.00
Private Label	0.52	0.36	0.01	1.00
Chain Level				
Tropicana	0.82	0.17	0.62	1.00
Florida Natural	0.77	0.18	0.58	1.00
Minute Maid	0.78	0.24	0.38	1.00
Private Label	0.66	0.31	0.17	1.00
Frozen Orange Juice				
National Level				
Minute Maid	0.28	0.26	0.00	0.87
Old Orchard	0.49	0.18	0.09	0.97
Private Label	0.33	0.23	0.00	0.82
Market Level				
Minute Maid	0.38	0.25	0.13	0.73
Old Orchard	0.58	0.13	0.39	0.83
Private Label	0.34	0.29	0.06	0.73
Chain Level				
Minute Maid	0.37	0.15	0.16	0.56
Old Orchard	0.60	0.14	0.45	0.83
Private Label	0.37	0.10	0.22	0.51

Notes: Average, standard deviation, minimum and maximum of the correlation coefficients between stores that are at the national level, in the same market, or in the same chain.

Table 4

Probit: Probability of Sale of Refrigerated Orange Juice

(Price Less than 75% of the Mode Price)

	Sale of Product			
	Tropicana	*Florida Natural*	*Minute Maid*	*Private Label*
Weeks elapsed since the last sale for product in a given store				
Tropicana	-0.089*	-0.05	-0.134*	-0.01
	(0.025)	(0.025)	(0.061)	(0.025)
Florida Natural	-0.042	-0.05	-0.117*	0.022
	(0.040)	(0.039)	(0.057)	(0.041)
Minute Maid	0.038	-0.01	-0.021	0.041
	(0.029)	(0.025)	(0.032)	(0.029)
Private Label	0.108	-0.04	0.008	-0.11*
	(0.045)	(0.039)	(0.044)	(0.039)
Weeks elapsed since the last sale for product in a given market				
Tropicana	0.098*	0.059	0.18*	-0.01
	(0.038)	(0.044)	(0.076)	(0.061)
Florida Natural	0.035	0	0.131*	-0.04
	(0.042)	(0.043)	(0.059)	(0.044)
Minute Maid	-0.077*	0.015	-0.009	-0.05
	(0.033)	(0.031)	(0.037)	(0.040)
Private Label	-0.109*	0.01	0.003	0.053
	(0.047)	(0.047)	(0.045)	(0.046)
Constant	0.428	-0.33	-1.262	-0.9
	(0.963)	(0.768)	(1.406)	(1.098)

Notes: Number of observations = 2,288. Coefficients for the store and weekly dummies are not reported. Asymptotic standard errors are in parentheses. An "*" indicates that we can reject the null hypothesis at the 5 percent level.

Table 5

Probit: Probability of Sale of Frozen Orange Juice

(Price Less than 75% of the Mode Price)

	Sale of		
	Minute Maid	*Old Orchard*	*Private Label*
Weeks elapsed since the last sale for product in a given store			
Minute Maid	0.027	-0.025	-0.023
	(0.024)	(0.013)	(0.014)
Old Orchard	-0.144*	-0.025	-0.011
	(0.041)	(0.015)	(0.017)
Private Label	-0.014	0.036	-0.026
	(0.046)	(0.025)	(0.023)
Weeks elapsed since the last sale for product in a given market			
Minute Maid	-0.001	-0.047*	-0.005
	(0.036)	(0.024)	(0.021)
Old Orchard	0.19*	-0.007	0.04
	(0.050)	(0.027)	(0.023)
Private Label	0.055	-0.086	-0.053
	(0.076)	(0.045)	(0.049)
Constant	1.382	-0.496	0.848
	(1.134)	(1.537)	(0.840)

Notes: Number of observations = 1,040. Coefficients for the store and weekly dummies are not reported. Asymptotic standard errors are in parentheses. An "*" indicates that we can reject the null hypothesis at the 5 percent level.

Table 6

Summary of Granger Causality Test Results (α = 5%)

Refrigerated Orange Juice

Price of	*Granger causes*	*Price of*	*% of stores*
Tropicana	→	Florida Natural	63.64
	→	Minute Maid	36.36
	→	Private label	50.00
Florida Natural	→	Tropicana	50.00
	→	Minute Maid	36.36
	→	Private label	45.45
Minute Maid	→	Tropicana	36.36
	→	Florida Natural	40.91
	→	Private label	45.45
Private label	→	Tropicana	31.82
	→	Florida Natural	31.82
	→	Minute Maid	27.27

Frozen Orange Juice

Price of	*Granger causes*	*Price of*	*% of stores*
Minute Maid	→	Old Orchard	60.00
	→	Private label	60.00
Old Orchard	→	Minute Maid	60.00
	→	Private label	30.00
Private label	→	Minute Maid	30.00
	→	Old Orchard	20.00

Table 7

Number of Stores in which Impulse Response is Greater than Half of the Impulse

Refrigerated Orange Juice

		Stores with Response > ½ Impulse	
Impulse Brand	*Response Brand*	*Number out of 22*	*Percentage*
Tropicana	Tropicana	5	23
Tropicana	Florida Natural	4	18
Tropicana	Minute Maid	2	9
Tropicana	Private label	6	27
Florida Natural	Tropicana	2	9
Florida Natural	Florida Natural	10	45
Florida Natural	Minute Maid	2	9
Florida Natural	Private label	6	27
Minute Maid	Tropicana	6	27
Minute Maid	Florida Natural	7	32
Minute Maid	Minute Maid	13	59
Minute Maid	Private label	9	41
Private label	Tropicana	2	9
Private label	Florida Natural	2	9
Private label	Minute Maid	3	14
Private label	Private label	8	36

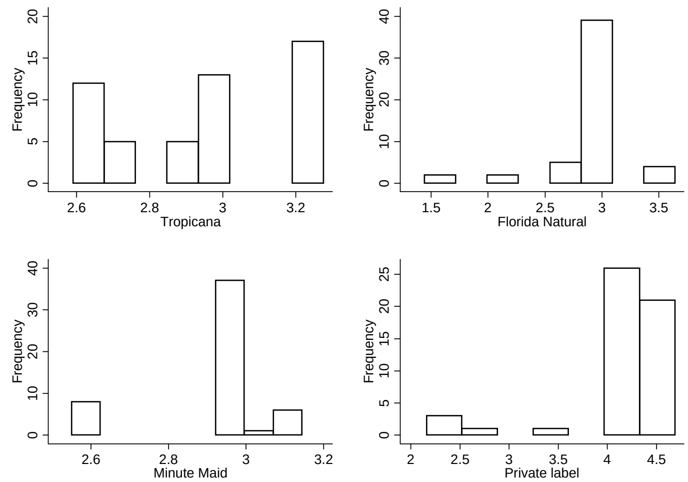
Frozen Orange Juice

		Stores with Response > ½ Impulse	
Impulse Brand	*Response Brand*	*Number out of 10*	*Percentage*
Minute Maid	Minute Maid	1	10
Minute Maid	Old Orchard	2	20
Minute Maid	Private label	2	20
Old Orchard	Minute Maid	1	10
Old Orchard	Old Orchard	3	30
Old Orchard	Private label	0	0
Private label	Minute Maid	1	10
Private label	Old Orchard	1	10
Private label	Private label	2	20

Figure 1

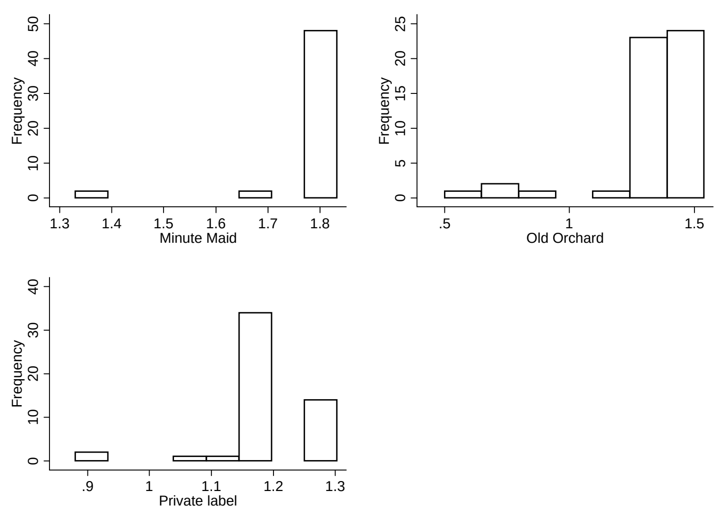
Histograms of Orange Juice Prices in Representative Stores

Refrigerated Orange Juice



Note: Values are 1998 prices for 64 fl. oz. cartons of refrigerated orange juice.

Frozen Orange Juice



Note: Values are 1998 prices for 12 fl oz. containers of frozen orange juice concentrate.

Figure 2

Frozen Orange Juice Impulse-Response