Retail Pricing Patterns and Driving Factors of Price Variation

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Abstract

This study explores the strategic pricing behaviors across retail chains for produce products. We adopt a Panel-VAR model to identify the driving factors of retail price variation and find that retail price history, competition, product cost are among the key drivers of retail price change. Forecast Error Variance Decomposition (FEVD) is used to quantify the relative impact of driving factors to retail price changes and show how they affect prices differently across retail chains. We also find that higher responsiveness to competition may indicate superior management ability in price setting that associates with better profitability in practice.

Keywords   Retail Pricing Strategy, Price Driver, Panel-VAR, Retail Competition

JEL code   Q11, Q13

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I. Introduction

The conventional model of retail pricing for produce products assumes retailers set price equal to the farm price plus a certain markup (George and King, 1971; Gardner, 1975; Heien, 1980; Wohlgenant and Mullen, 1983; Elitzak, 1996; Wohlgenant, 2001). More recent studies (Sexton, Zhang and Chalfant (SZC), 2003; Hosken and Reiffen, 2004) recognize the large degree of price dispersion as a major characteristic of grocery retail pricing. Some studies suggest that retail price variations often reflect changes in retail margins, rather than changes in costs (Conlisk, Gerstner and Sobel, 1984; MacDonald, 2000; Pesendorfer, 2002; Hosken and Reiffen, 2004). However little has been done to characterize the overall pattern of retail pricing behavior, even less effectively identify and quantify the driving factors behind retail price variation.

Using the scanner dataset with 15 retail chains for six produce products, Li (2010) find strong evidence of retail price dispersion. The observed pricing behaviors are categorized into four leading patterns, namely Markup pricing, Fixed pricing, Periodic sale, and High-low pricing. To a large extent retail prices no longer reflect efficiently on changes to product cost.

What are the driving factors behind retail price change for produce products and how do they influence retail price variation? This question is key to understanding retailer's strategic pricing behaviors and the dynamics of the food industry. But finding the answer to this question can be challenging due to the complexity of price setting behavior itself.

Using a Panel-VAR model, we identify the key drivers of retail price variation and quantify their relative impact to different types of retailers. We further link retailer's pricing practice to their profitability, and find that higher responsiveness to competition may indicate superior management ability that associates with better profitability in practice. This paper contributes to related literature by innovatively applying Panel-VAR method to the price analysis of produce products, and provides insights about the strategic behaviors behind retail price decisions across retailers.

The paper is structured as follows: section 2 describes the data and shows evidence of retail price dispersion; section 3 explores the driving factors of retail price variation using Panel-VAR model; section 4 presents the relative impact of driving factors to retail price variation for

different types of retailers and draws implication to relative profitability. Section 5 concludes the paper.

II. Data and Evidence of Retail Price Dispersion

The dataset provided by Information Resources Inc. (IRI) contains retailer scanner data on weekly retail prices, volume and dollar sales from 1998 to 1999. There are 20 chain-location combinations in the full data sample. The markets cover a substantial geographic cross-section of the national market, which include Albany, NY (two chains), Atlanta (three chains), Chicago (three chains), Dallas (five chains), Los Angeles (LA, four chains), and Miami (three chains). Six major produce products are included in the study: apples, grapes, grapefruit, iceberg lettuce, oranges, and tomatoes. Table1 shows a subset of products and varieties included in the dataset. Farm-level price data are also available from the USDA Federal-State Market News Service (F-SMNS). One advantage of this dataset is that it not only contains information from multiple retail chains at multiple locations, but it also has information of multiple chains operating at the same city, which enables the comparison at disaggregated level retail price variations across chains, across locations, and across commodities.

Table 1. Summary of Product Varieties and Price Look Up (PLU) Codes

Index	Category	PLU	Variety
1	Apple	4131	Fuji
		4021	Golden Delicious (GD)
		4016	Red Delicious (RD)
2	Grapefruit	4027	Ruby Red
3	Grape	4022	Green Seedless
		4023	Red Seedless
4	Lettuce	4076	Green Leaf (GL)
		4061	Iceberg (IB)
		4640	Romaine (Rom)
5	Orange	4012	Navel, Small
		3107	Navel, Large
6	Tomato	4087	Plum
		4664	Bulk
		4799	Greenhouse (GH)
		4805	Vine Ripe (VR)

Comparing across commodities at a give location, some chains indicate strong uniform chain level strategic pricing behavior across all commodities. Some of these chains never change retail prices for all the commodities in our sample for the entire two-year period. Some chains only adjust price once or twice for most of the commodities in our data sample, which may indicate a rough adjustment on the expected retail margin.

Comparing across locations, there are large differences across cities. For example, for all observations at Albany 86.64% of the times prices are at the mode price; but for all the chain stores at LA on average only 20.97% of the times prices are at the mode price. In addition, there are cases where some retail chain operates at multiple cities and exhibits different pricing behaviors. For example, Chain 1 sells iceberg lettuce at both Dallas and LA. There are more frequent downward price variations at Dallas, yet the mean price at LA is much lower than the mean price in Dallas. This may serve as possible evidence that a specific chain apply multiple pricing strategies at different locations after removing the effect of possibly differentiated product cost.
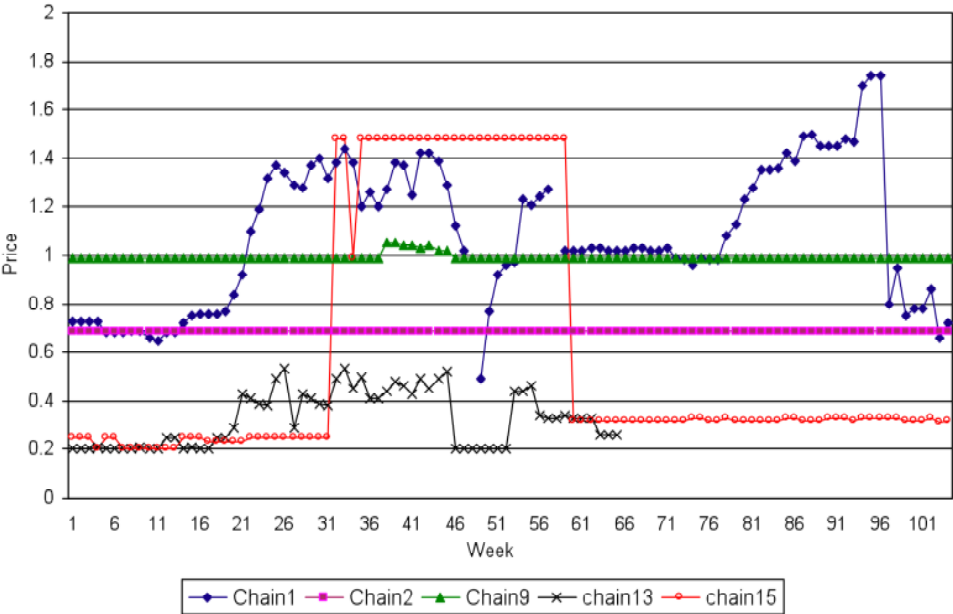
Figure 1: Price Variations for Green Seedless Grapes Among Dallas Chains

Most interestingly, comparing across chains at the same location, where we can reasonably assume farm price for a given commodity to be the same, we still observe systematic differences for pricing behaviors across chain. Figure 1 shows retail price series for green seedless grapes among chain 1, chain 2, chain 9, chain 13, and chain 15 at Dallas. Chain 2 and 9

have mostly fixed prices through the time period, whereas the other chains have frequent price variations. Many examples can be found in the scanner dataset that provide strong evidence about the existence of different pricing strategies adopted by different chains.

Large degree of price dispersion at chain level can further be seen from table 2 below: to one extreme some chains price their product 100% of the time at the mode price (Chain 2, 5, 6 and 11), meanwhile almost all the other chains (except chain 10) have less than 50% of the time prices are the same as the mode price, 6 out of the 15 chains price their product less than 30% of the time at the mode price (chain 1,7, 8, 12, 13, 14).

Table 2: Percentage of Observations at Mode Price, below or above Mode by 10% or 20%, by Chain

Chain	<mode by20%	<mode by 10%	% at mode	>mode by 10%	>mode by 20%
1	16.76	24.06	17.87	24.71	17.41
2	0	0	100	0	0
3	13.33	18.44	49.08	16.24	11.7
4	2.72	3.42	95.32	0	0
5	0	0	100	0	0
6	0	0	100	0	0
7	5.11	11.38	26.28	18.89	11.26
8	18.39	26.86	23.26	20.25	15.2
9	5.81	13.79	31.46	21.23	14.82
10	19.61	23.65	53.59	13.92	13.02
11	0	0	100	0	0
12	34.31	36.27	25.49	29.41	29.41
13	8.7	18.53	26.1	25.65	22.71
14	24.8	32.44	22.5	13.46	9.76
15	20.24	27.4	44.02	16.42	12.03

The observed pricing behaviors is categorized into four leading patterns, based on statistic specification such as the frequency of price change, the direction, magnitude, duration of price variation, and the correlation between retail price and farm price (table 3). These leading pricing patterns are:

a) ***Markup pricing***: Retailers who utilize markup pricing strategy set the markup fixed or fixed proportional to the acquisition costs. Retail price movement efficiently reflects the changes of supply and price at the farm level. Although it is not to expect that any price series will reflect the exact mark-up pricing behavior as described in economic theory, our data do show that some chain stores have much higher correlation between retail price and farm price than others. For example, the price correlation coefficient for chain 15 at Miami is as high as 0.79, whereas the price correlation for chain 11 at either Miami or Atlanta is only 0.4. Chain 15 at Miami is identified as adopting the markup pricing strategy.

b) ***Fixed pricing***: The retail price is fixed at a certain level regardless the fluctuation of farm price. One widely adopted marketing practice, known as every day low price (EDLP), is an example of fixed pricing. Under EDLP prices are fixed for extended periods of time and the frequency of promotional sales or discounts is very low if not totally impossible. In our dataset, 5 out of the 15 retail chains (chain2, 4, 5, 6, 11) display a strong inclination for fixed pricing strategy in the sense that more than 95% of the times their prices fix at its modal price during the 104 week periods.

c) ***Periodic sale***: The retail price stays at a certain level for extended periods, interrupted by temporary price discounts, after which the price returns to its original level. In this case, a single "regular" price or several mass point prices exist. The "weekly special" pricing practices seen in some retail market exhibit the main characteristics of periodic sale. In our data, the price variation for chain1, 3, 7, 9, 10, 13 and chain 15 (at Atlanta and Dallas) can be characterized as periodic sale. [1] Instead of having a single "regular" price, most of these chains in practices have several mass point prices. Chain 3 and 10 have relatively larger percentage of time (about 50%) price sticks to its mode price[2]. Most of these chains have more downward pricing variation from the mode price than upward price variation. It is important to note that although retailers put some basket of products on sale every week, the choice of sale commodities can vary from week to week.

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[1] Chain 15 operates in three different cities in our dataset, Atlanta, Dallas and Miami. It shows that chain 15 adopts at least two different pricing strategies, namely periodic sale at Atlanta and Dallas, and markup pricing at Miami.

[2] Chain 3 and 10 typically adopt periodic sale for most of the products in our data sample, except for grape where there are much more price variation than other products they carried.

d) ***High-low pricing***: Price fluctuates frequently among different high and low levels. The mean of the prices may be relatively higher than fixed price, but the actual price varies constantly. In general, the downward price deviation from the modal price will be smaller under high-low pricing case than those under periodic sale pricing strategy. Chain 8, 12, 14 likely adopt high-low pricing strategy in the sense that their price vary frequently, and the number of different prices is higher than those characterized by periodic sales. In addition, price increases from the mode often outweighs price decreases, either in terms of time or magnitude.

Fixed price can be easily identified and normally has lower mean price than other price categories at a given location. The difference between high-low pricing and markup pricing is that the price variation of the former shows no close correlation with the farm price variation, but the later does. The difference between high-low pricing and periodic sale is that the former has relatively more frequent price variation and usually does not have a regular price or few mass point prices.

Table 3: Price Correlation Between Retail Price and FOB Price

Chain Product	1 Dallas	1 LA	3 Atlanta	7 Chicago	8 LA	9 Dallas	10 Albany	12 LA	13 Dallas	14 LA	15 Miami	15 Atlanta
Orange Navel	0.46	0.44	0.13	0.59	0.56	0.54	-0.14	0.31	-0.53	0.19	0.50	0.00
Lettuce IB	0.40	0.72	-0.01	0.26	0.45	0.62	0.63	0.52	0.21	0.46	0.53	0.78
Lettuce GL	0.62	0.87	0.55	0.61	0.63	0.87	0.79	0.69	0.21	0.68	0.64	0.82
Lettuce Rom	0.63	0.77	0.56	0.33	0.48	0.74	0.72	0.69	0.13	0.66	0.70	0.75
Apple Fuji	0.33	-0.01	0.27	-0.03	0.43	0.02		-0.32	-0.32	0.62	0.45	0.65
Apple GD	-0.36	-0.27	0.39	0.13	0.19	-0.05		-0.46	0.61	0.01	0.33	0.10
Apple RD	-0.39	-0.38	0.11	0.34	0.03	0.43		-0.02	-0.06	0.60	0.24	0.45
Grape Green	0.75	0.64	0.67	0.42	0.51	0.65		0.69	0.79	0.72	0.54	0.68
Grape Red	0.51	0.53	0.50	0.42	0.23	0.61		0.47	0.18	0.42	0.36	0.37
Grapefruit	-0.55	-0.01	0.19	-0.23	0.40	-0.05	-0.63			-0.01	0.20	0.64
Tomato Plum	0.79	0.80	0.74	0.40	0.51	0.79		0.29	0.49	0.65	0.43	0.73
Tomato VR	0.19	0.24		0.15	0.38	0.50		-0.07	0.43	0.40	0.46	0.62
Tomato GH	0.38	0.01	0.47	-0.52	0.18	0.38		0.27	-0.20	0.26		

Notes: Blank cells indicate varieties that were unavailable at the chain. See table 1 for commodity abbreviations.

This finding contradicts the traditional model of retail pricing of farm products, which predicts that retail prices reflect the underlying farm prices and respond to supply shocks efficiently; in practice retailers set prices based on diversified pricing strategies. Most

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interestingly, the retail price variations under alternative pricing regimes often have little correlation with the farm price. Considering modern groceries sell a vast number of different products, retailers may well be acting rationally in using these stylized retail price behaviors as marketing strategies to attract and retain customers in order to maximize their total profit.

Marketing studies often characterize retailers by one of the two groups: Everyday Low Price (EDLP) practitioner or High-Low Price (HL) practitioner, based on whether or not retailers frequently change their prices in practice. But the question is: in terms of understanding retail pricing behavior, will it be sufficient to simply pool all the retailers who change their prices into one big group. It is like dividing people in the world by those who can read or those who cannot read, and ignore the fact that many different languages are used for communication. We see strong evidence of price dispersion across chains in the data and clearly different retailers may adjust price differently for the same product sold at the same week in the same city. To better understand the strategic pricing behaviors across retailers, one needs to take a closer look within the group of retailers who changes their prices and ask: What are the key driving factors of retail price variation? How do the driving factors affect retail price differently for different types of retailers?

III. Identify the Driving Factors of Retail Price Variation

Attempts have been made by theoretical studies to explain retail price variation. The intertemporal discrimination model views retail price variation as mean of retailer price discrimination (Conlisk, Gerstner and Sobel, 1984; Sobel, 1991; Banks and Moorthy, 1999; Pesendorfer, 2000). The static model of retailer competition (Varian, 1980) argued the informed consumers purchase from the retailer offering the lowest price, but the uninformed consumers do not compare prices when doing their shopping. Varian shows that in equilibrium, all retailers randomly choose prices every period. The multi-product retailer model emphasizes the multiproduct characteristics of grocery retailers, and show that goods with independent demand may have interrelated price by the same retailer (Lal and Matutes, 1994; Hosken and Reiffen, 2001; Braido, 2006).

Meanwhile, existing empirical papers find the decision of sales may be affected by product popularity, inventory capacity, or time periods since last sale (Warren and Barsky, 1995;

Aguirregabiria, 1999; Pesendorfer, 2000; Chevalier, Kashyap, & Rossi, 2000). Menu cost may form a barrier of price changes at the micro level (Levy et al., 1997).

Marketing literature (Nagle and Holden, 1994; Levy, et al. 1997; Nijs, Srinivasan, & Pauwels, 2007) offer some practical insights on the determination of price change at retail level. The price decision in practice is based on information such as: wholesale price changes, promotions; latest store information on the product, which may include last week's sale and prices; competitors' prices and promotions; and menu costs.

While the above studies offer some insights about retail price determination, it remains a challenge to empirically confirm the driving factors of price variation and quantify their impacts, given the complexity behind the price decision-making process. Many factors enter into the process, which may include product price history, product cost, consumer demand, promotion by competitors, the price change for good that are close substitutes. On the other hand, movements of the retail price may also affect consumer demand, competitor's price and sales, etc. There are interactive feedback loops between the retail price movement and the driving factors. From research standing point, the availability of data and the right choice of econometric tool are crucial in order to capture the complex interactive feedback system. Luckily, the rich dataset used in this paper provides sufficient possibility to study the movements of retail price, demand, cost, and competition at the same time. Methodology-wise, we use a panel vector autoregressive model (Panel-VAR) to capture the complex interactive price systems.

The choice of model should best reflect the nature of the data and the underlining economics. Panel-VAR Model is better known in macroeconomics and finance literature for its ability to analyze time series data with interactive feedback loops. Panel VARs are able to (i) capture both static and dynamic interdependencies, (ii) treat the links across units in an unrestricted fashion, (iii) easily incorporate time variations in the coefficients and in the variance of the shocks, and (iv) account for cross sectional dynamic heterogeneities. (Canova and Ciccarelli, 2013). In this study, VAR model is a capable tool to capture complex interactions among retail prices and the driving factors, while the panel structure incorporate additional information across product categories (Lütkepohl, 2005).

The equation below illustrates a VAR model used in this study. Retail price history of the commodity (P), Competitor's price (CP), Farm price (FP)[3], Retail demand or sales (D), and competitors' demand (CD) are included in the system. Practically, the VAR process may include more equations than the five specified here. Take LA for example, in our data sample there are four large retail chains operating in LA, so the impact of competitors' prices to each chain needs to be modeled by three separate equations, while the same logic applies to competitors' demand.

$$
\begin{bmatrix} P_{j,t} \\ CP_{j,t} \\ FP_{j,t} \\ D_{j,t} \\ CD_{j,t} \end{bmatrix} = \begin{bmatrix} \alpha_{P,t} \\ \alpha_{CP,t} \\ \alpha_{FP,t} \\ \alpha_{D,t} \\ \alpha_{CD,t} \end{bmatrix} + \sum_{k=1}^{K} \begin{bmatrix} \beta_{1,1}^k \cdots \beta_{1,5}^k \\ \beta_{1,1}^k \cdots \beta_{1,5}^k \\ \beta_{1,1}^k \cdots \beta_{1,5}^k \\ \beta_{1,1}^k \cdots \beta_{1,5}^k \\ \beta_{1,1}^k \cdots \beta_{1,5}^k \end{bmatrix} \begin{bmatrix} P_{j,t-k} \\ CP_{j,t-k} \\ FP_{j,t-k} \\ D_{j,t-k} \\ CD_{j,t-k} \end{bmatrix} + \begin{bmatrix} \varepsilon_{P,t} \\ \varepsilon_{CP,t} \\ \varepsilon_{FP,t} \\ \varepsilon_{D,t} \\ \varepsilon_{CD,t} \end{bmatrix}
$$

The panel parameter is product category and variety. More than a dozen product subcategories are included in the current study. One way to understand the whole Panel VAR structure is to picture stacking more than a dozen of the above system of equations together to run the estimation at the same time. Based on the data, chains often exhibit similar pricing strategies across sub-product varieties in the same category. For example, the three varieties of lettuce in our study (iceberg lettuce, green leaf lettuce, and Romaine lettuce) share very similar price patterns. On the other hand, sub category products can be viewed as substitutes to one and another, use product verity as panel help utilize the most information while also allowing for heterogeneity and interactions across the subcategory prices.

With increasing concentration and consolidation of the retail markets, the market structure can be best captured as oligopoly. The 2006 MSA (metropolitan statistical areas) CR-4 for retail industry in the US is 79.4%, which indicates in general the largest four retailers account for 80% of the retail market share. This oligopoly structure will be especially true in large cities, like the ones included in our study (Chicago, New York, LA, etc.). Although Panel-VAR model

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[3] We don't have access to wholesale price, instead we use farm price to approximate the impact of changes in product cost to retail price. This won't cause a big problem for our study, since a good majority of the produce products are distributed through direct buy. The links between farm gate and retail market are relative shorter compared to most manufactured goods.

does not require the specification of market structure, the knowledge that a large percentage of the market share are captured by the retailers in the dataset increases the reliability of the findings about market competition.

The focus at this stage of data analysis is mainly for periodic sale and high-low pricing retailers. Fixed pricing retailer in general do not change their prices, so there is very few needs to identify driving factors to price change for this type of retailer. And it is clear that fixed pricing retailer tends to ignore the price shocks in the farm market and does not respond to competition. While for markup pricing retailers, the arbitrary definition is that there is high correlation (more than 60%) between the retail price and product cost, and retail price change to a large extent reflect changes of product cost.

Several steps are undertaken for the data analysis. First we carried out the panel unit root test using method developed by Levin, / Lin and Chu (2002) to rule out none stationary time series problem. The test may be viewed as a pooled Dickey-Fuller test. Second, we use Panel-VAR to identify the driving factors of retail price variation. The specified estimation is system GMM. Next, impulse response functions and forecast error variance decomposition (FEVD) are used to quantify the relative impact of driving factors on price change (Lütkepohl, 2005; Love, 2006). Lastly, we relate retailers' different pricing behaviors to their relative market share and profitability to draw implication on pricing performance.

Findings from Panel VAR results on the overall and subsamples of the data indicate: there are strong evidence that the past retail price history, cost of the product, competition, and consumer demand play important roles in determining retail price variation. Meanwhile, the relative importance of different factors to price movement varies across retail chains. Detailed results on the relative importance of the driving factors are reported in next section.

IV. **Quantify the Impact of Driving Factors of Retail Price Variation**

Forecast Error Variance Decomposition (FEVD) analyses help to quantify the relative importance of the driving factors to retail price variation. Figure 2 shows the results for four

different retail chains in LA across all product categories. Among these retail chains, Chain1 is periodic sale type of retailer, the other three chains (2, 12, and 14) are high-low pricing type retailers. Recall that the CR4 in retail industry for metropolitan statistical areas is about 80%. Although the data did not include all retail markets in LA, the chains included accounts for a large percentage of the market share, which enable use to capture the essence of retail competition is the region.
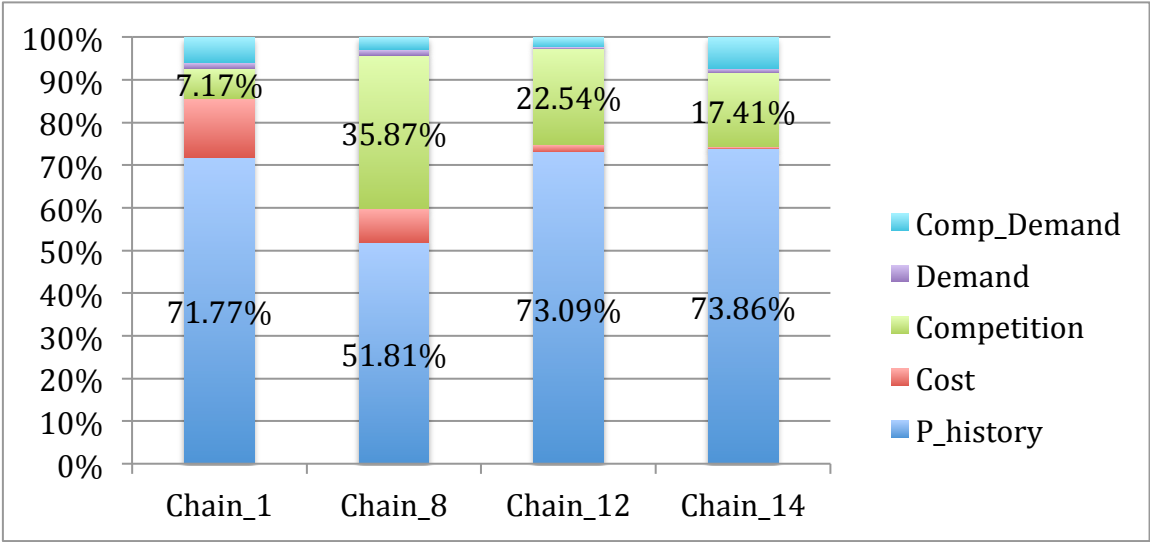

Figure 2: Relative Impact of Retail Driving Factors (all products)

In general, price history (P_history) plays an important role in determining retail price variation. The impact of product cost (cost) and competitor's price (competition) are different across retailers. Chain1 places much higher emphasis on product cost, which account for 14% of its retail price variation, whereas for the three high-low price retailers, shocks of product cost on average only reflect 3% of the retail price changes. There are significant differences in the way these retailers respond to competition. While price variation by competitors only reflects 7% of chain1's price adjustment, the other three chains are at least twice more responsive to competitions.

Figure 3 reports the results from FEVD using panel of three varieties of lettuces (Iceberg, Green Leaf, and Romaine) instead of the full panel. Comparing Chain1 with the other three chains, again we see strong evidence that the high-low price retailers place much more emphasis on price response to competition than does the periodic sale retailer.
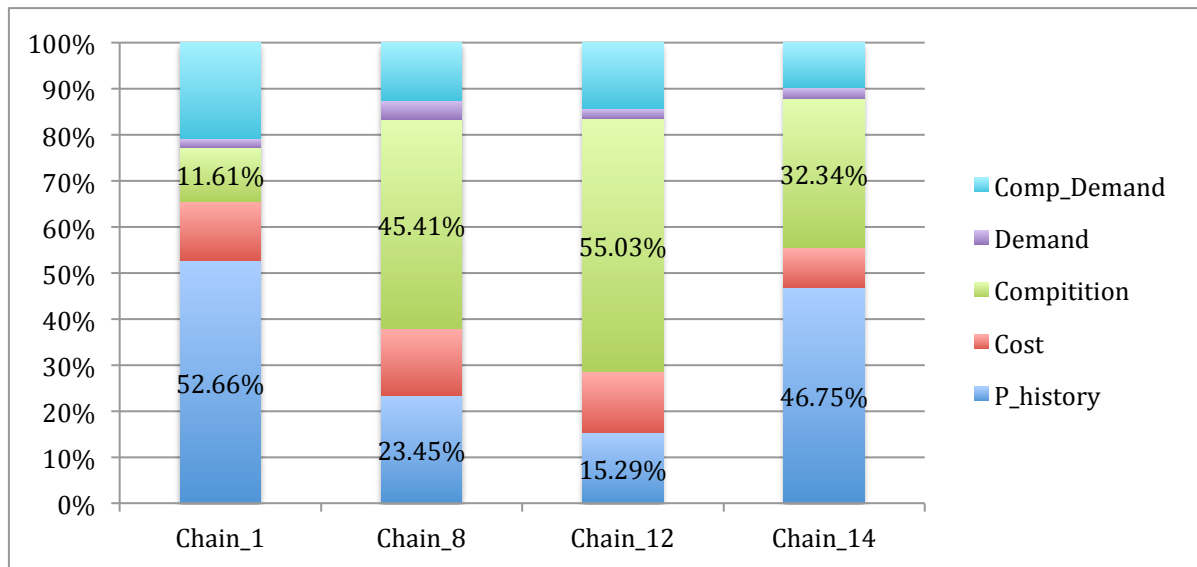
Figure 3: Relative Impact of Retail Driving Factors (lettuces only)

The FEVD results provide evidence that high-low pricing retailer in general tend to respond more actively to retail competition than periodic sale retailers. The next question one want to ask is: whether different pricing practices actually reflect differences in marketing and management ability, and results in different level of profitability.

Table 4: Relative Market Share v.s. Relative Profit

	Relative Market Share	Relative Profit
Chain_1	19.02%	13.69%
Chain_8	23.82%	26.88%
Chain_12	24.92%	25.12%
Chain_14	32.24%	34.32%

For the products included the dataset, we calculate the relative market share and the relative profit for each of the retail chains in LA (table 4). Interestingly, we found that chain1, the periodic sale retailer, takes about 19% of the relative market share, but only earns less than

14% of the relative profit, whereas chain2, 12 and 14 all earns better share of profit compared to their relative market share. This result suggests that higher responsiveness to market competition may imply better management and profitability in practice.

V. Conclusions

This study explores the strategic pricing behaviors across retail chains for some major produce products. We innovatively adopt a Panel-VAR model to identify the driving factors of retail price variation. Retail price history, competition, and farm price are among those identified as important drivers of retail price change, and they tend to have different impact to different types of retailers based on the FEVD results.

Marketing research, that simply divides retailers to those who do not change prices and those who do, is not sufficient to understand the ambiguous and diversified pricing behaviors across retail chains. Among those retailers who do change retail prices, their pricing decision reflect different marketing emphasis and management considerations, and leads to different profitability. We find evidence that higher responsiveness to competition may indicate superior management ability that translates into better profitability in practice.

This study is among the first to use Panel-VAR model to study the pricing dynamics in retail markets for perishable produce products. It is also among the first to identify and quantify the driving factors of retail price variation for these products. Our innovative way to categorize retailer strategic pricing behaviors leads to improved precision in understanding diversified retail pricing strategies.

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