Complex Interactions and Strategic Pricing of Brand-Level Nut Products in the United States: A Graph Theoretic Approach

by

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Abstract

Nuts such as almonds, pecans, walnuts, and pistachios are available in the U.S. market in different forms and brands. There are well-known national brands as well as not-so well-known private label and store brands. Nut producing firms compete for market share and strategically price, brand, advertise and position products in the market. Conventional brand-level analysis of such markets is achieved through calculation of market power and price cost margins assuming the presence of pure strategy Bertrand-Nash Equilibrium in prices. This is supported by a set of prior assumptions with regards to the structure of the market and oftentimes these are too restrictive, because pricing decisions are made in a complex multivariate situation with numerous interactions between variables that determine the prices and prices themselves. In this study, using 2015 Nielsen scanner data for nut products, complex causal relationships among brand level prices are estimated using cutting-edge machine learning algorithms. Also within this method, the concept of Markov Blankets is used to identify specific brands that are immediately important for a given brand. Several national brands were identified as a direct cause of the price of store brands. Even though store brands were associated with the highest market share, they had no influence on any other brands' pricing decision and strategy.

Keywords: Directed Acyclic Graphs, Nuts Prices, Brand Level, Machine Learning

JEL Classification: C40, D83, D12

Introduction

Nuts provide high energy and contain more dietary fiber, vitamins, minerals and unsaturated fat compared to other salted snacks. According to the findings of Nielsen et al. (2014), about two-fifths of adults in the United States consumes nuts or seeds products on a regular basis. Nuts has been introduced in to consumers daily life as a part of nutrient intakes. The association between nuts consumption and its health benefits has already been approved by many studies, including its benefit for heart disease, being recommended into daily consumption, and preventing obesity (King et al. 2008; Kris-Etherton 2008; Dietary Guidelines 2015-2020). In the extant literature, previous studies have already examined the demand of various nuts products (Lee 1950; Lener 1959; Dhaliwal 1972; Russo et al. 2008; Cheng, Dharmasena, and Capps 2018), forecasted prices of single or multiple nuts products (Shafer 1989; Florkowski 2008), and since the production of nuts products differs regionally, several studies examined them particularly (Crespi and Chacon-Cascante 2004; Kim and Dharmasena 2017). The price elasticities were estimated, prices were forecasted using different techniques, and regional market power and structure were examined. However, at present, no studies have looked at the nuts market with regards to the competition, market power, and strategic relationships between national brands and store brands. The general objective of this study is to investigate the complex causal relationships among prices and quantities at various brand levels for nut products using cutting-edge machine learning algorithms.

This study is organized as follows. The data used in the analysis was discussed in the first section. Second, we explain the machine learning algorithms along with the Direct Acyclic Graphs. Third, we provide the empirical results on the causal relationships revealed from those graphs and estimated coefficients. Finally, concluding remarks and limitations are discussed.

Data

The data used in this study are weekly observations derived from the Nielsen Homescan Panel 2015[1]. We categorized brands of peanuts and tree nuts based on product module codes and brand modules provided by Nielsen. We ended up with 547 different brands from Nielsen Homescan. Eventually, top ten brands based on market share in 2015 were used in the analysis.

In the Nielsen Homescan Panel, purchases of nuts are reported for each household over time, including the amount paid in dollars, the coupon value in dollars, and the amount purchased in ounces. Initially, we generated weekly purchases and sales of nuts made by households for each brand. Next, the monetary values and net of coupon values paid by all households were summed to derive sales for the respective brands per week. As well, the amount purchased was summed up over all households for each week for the respective brand. The sales and quantity data are expressed in terms of dollars and ounces purchased by all household per week. Next, we ranked the sales value in descending order and picked the top ten brands[2].

Further, we calculated the weekly unit prices for each brand by dividing weekly sales by weekly quantities purchased. In all, we developed weekly unit prices ($/ounce) and quantities (ounces) for ten brands, a total of 53 observations for each brand in the United Stated represented by the households selected by Nielsen.

Descriptive Statistics

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[1] based on data from The Nielsen Company (US), LLC and marketing databases provided by the Kilts Center for Marketing Data Center at The University of Chicago Booth School of Business. The conclusions drawn from the Nielsen data are those of the researchers and do not reflect the views of Nielsen. Nielsen is not responsible for, had no role in, and was not involved in analyzing and preparing the results reported herein.

[2] Per data use agreement, names of the brands are not revealed. However, we are able to identify and differentiate national brands and store brands and discuss the brands as Brand 1, Brand 2, etc.

Table 1 represents the descriptive statistics of prices and quantities of the top 10 brands of nut products. Since actual brand names are not revealed per data use agreement, we renamed all nut brands with the numbers from 1 to 10 in the order of market share, 1 being the highest and 10 being the lowest. Brand1 is the store brands, and has the highest market share and quantity, and has unit price with thirty-three cents per ounce. All of the other brands are national brands, where brand 3, 6, and 8 are associated with the highest unit price, about sixty cents per ounce. The brand with the lowest market share sold about 900 ounces per week on average.

<Insert Table 1 Here>

The correlation matrix of unit prices and quantities are represented in Table 2, 3, and 4.

<Insert Table 2, Table 3, and Table 4 Here>

Also, we show the market share in terms of national brands and store brands. As shown in Figure 1, store brands in Nielsen Homescan Panel 2015 has about 40% of the total market share. And the top 10 brands out of 547 brands occupied 85% of the total market share (Figure 2). And out of the top 10 brands of nut products, store brand has nearly half of market share (Figure 3).

<Insert Figure 1, Figure 2, and Figure 3 Here>

Methods

In order to search the relationship between national brands and store brands in terms of price and quantity, we utilized two machine learning algorithms Greedy Equivalence Search (GES) (Chickering 2002) and Linear non-Gaussian Orientation Fixed Structure Rule Three (LOFS R3). The GES algorithm builds a graphical casual structure while the LOFS R3 algorithm directs the undirected edges after the initial GES run. The Directed Acyclic Graphs (DAG) that represent the causal relationships among prices and quantities were determined by aforementioned algorithms in Tetrad 6.3.4.

Following explanation on DAGs is adopted from Bessler (2002), Pearl (2000), and Dharmasena, Bessler, and Capps (2016). A directed graph is and ordered triple {**V**, **M**, **E**} where **V** is a non-empty set of variable or nodes, **M** is a non-empty set of symbols attached to the ends of undirected edges, and **E** is a set of ordered pairs (edges). If we have a set of variables (nodes) {X, Y, Z}, a directed graph only contains directed edges, like X → Y, or Z → Y. An undirected edge, like X – Y will not be included and used to delineate the causal relationship between variables or nodes.

The DAG is a graph that only included acyclic relationship that will not start and end with the same variables or nodes. For instance, X → Y → Z →X will not be used or included in a DAG, since the variable (X) cannot be the cause of itself.

Three main types of DAG will be used and revealed in the analysis, including causal chains, causal forks, and inverted causal forks. A causal chain is where a causal ordering in variables will be observed, like X → Y → Z. The interpretation of this chain is that X causes Y and Y causes Z, or X causes Z through Z. A causal fork implies that a variable would be the common cause of other variables, like X ← Y → Z, where Y causes both X and Z. An inverted casual fork also called collider implies that two variables causes the same other variable, like X → Y ← Z, where both of X and Z cause Y. The causal relationships among prices and quantities of different nut brands will be mainly interpreted using these three types of DAG in the following section.

We used two machine learning algorithms to product the Directed Acyclic Graphs. The first one is Greedy Equivalence Search (GES) algorithm created by Chickering (2002). Three assumptions of GES are needed to empirically produce a DAG: 1) Causal Sufficiency Condition, no outside variables could cause any of the include variables; 2) Causal Markov Condition, any variables caused by their parents that take in all of the information from their grandparents; 3) Causal Faithfulness Condition, an undirected edge might arise then there is no causal relationship between two variables even if they are correlated (Dharmasena *et al.* 2016; Senia *at al.* 2017).

Most of the edges will be directed using GES search algorithms. However, it is also possible that undirected edges might arise in DAG even if there is certain relationship between variables (Kim and Dharmasena 2017). In order to tangle this situation, the second machine learning algorithm we used in the analysis is the Linear non-Gaussian Orientation Fixed Structure (LOFS) along with its R3 rule. R3 is one of iterations of LOFS. The LOFS R3 rule checks whether the sum of the Anderson-Darling statistic of residuals from the regression of one variable on another one and the Anderson-Darling statistics of the second variable is larger than the sum of the Anderson-Darling statistic of residuals from the regression of the second variable on the first one and the Anderson-Darling statistic of the first variable (Senia *et al.* 2017). If this is true, the LOFS R3 rule directs the edge from the second variable to the first one. If this is true on the reverse relationship, the direction of edge will be flipped to be from the first variable to the second one.

To focus on the price and quantity of store brands, we take advantage of the Markov Blankets (Pearl 2000) to determine the parents and children of the price and quantity of stores brands. Through the Markov Blanketing, we are able to uncover causes of store brand and national brand prices and quantities.

Results

In order to construct causal relationships among prices and quantities variables, we utilized the two machine learning algorithms to produce DAG for prices and quantities with and without prior knowledge. The overall objective of this study is to investigate the relationships between store brands and national brands in terms of prices and quantities. In this section, we focus on the causal relationships that originates from prices and quantities of store brand or ends with prices and quantities of store brands. Figure 4, 5, 6, 7 showed that, the prices of store brands were caused by the price of brand 2, the quantity of brand 5, and quantity of brand 6, regardless of the fact that we looked at only prices, prices and quantities taken together, or we imposed prior knowledge or lack thereof. The causal patterns regarding the price of store brands remain constant. The prices of store brands are caused by aforementioned variables and cause nothing. The case was somewhat different for the quantity of store brands, that the caused variables of the quantity of store brands did not change no matter we included prices and imposed prior knowledge or not. The quantity of store brands causes the quantity of brand 2 and brand 3 for sure. However, the cause of the quantity of store brands was sensitive to the included variables and prior knowledge imposed (Wand and Bessler 2016). The quantity of brand 7 is one of the parents of the quantity of store brands regardless of assumptions.

In the next step, we explored the dynamic relationships among prices and quantities variables by including the prices and quantities from previous week by lagging them both by one period. The DAG produced by using GES and LOFS R3 rule was shown in Figure 9. Still, focusing on store brands, the causes of the price of store brands were the price of brand 2, the quantity of brand 6, and the lagged price of brand 4. Consistent with previous finding, the price of store brands did not cause anything else. The causes of the quantity of store brands were partially consistent with previous findings, including the quantities of brand 5, 7, 8. The casual relationship between the quantity of store brands and brand 3 was flipped. And the quantity of store brands still causes the quantity of brand 2.

The model statistics for each model were represented in Table 4.

Owing to the Tetrad package, we were able to perform Markov Blankets for the price and quantity of store brand. The results were demonstrated in Figure 10 for quantity, Figure 11 for price. The Markov blanket detects a variable with its children, its parents, and any parents of its children. This will render the variable conditionally independent from the rest of the graph. In essence, the Markov blanket of the node is the most important knowledge in predicting the behavior of a variable (Senia *et al.* 2017). As shown in Figure 10, the quantity of store brands has four parents, one children, and one grandparent. The parents were the quantity of brand 3, 5, 7, and 8. The children was the quantity of brand 2. One thing to be noteworthy is that the quantity of brand 7 was both the parent and grandparent of the quantity of store brands. Figure 11 represents the causal relationships centered on the price of store brands. The price of store brands has three parents and no children. The quantity of brand 6, the price of brand 2, and the price of brand 4 in the previous week caused the price of store brands.

Concluding Remarks

Store brands have been on the rise for not only nuts products but also for various other products. Even though the market share of store brands in the nut category is the highest, the pricing decision and strategy heavily depends on national brands. Without a set of prior assumptions with regards to the structure of the market, machine learning algorithms allow us to investigate the complex causal relationships at various brand levels for nut products. Store brands have the largest market share compared to national brands, but have no influence on the pricing decision and strategy of national brands. The highly complex causal relationships among national brands and stores brands in terms of pricing and quantity were demonstrated in this study under several scenarios where we imposed different knowledge and assumptions. Surprisingly, not much own-price and quantity relationships were revealed. Usually the price and quantity of one brand was caused by other brands, which makes the relationship among brands very complicated. There are several limitations of this study. Assumptions on causal sufficiency condition where selected variables make up the complex system might act as a limitation to the graphical causality model. However, this is a strong assumption regarding the pricing decision and strategy made by nuts manufacturers and retailers. Some other factors, such as advertisings, economic factors, and prices of other competing products, could be included in this analysis by bringing in more information. Second, only Nielsen Homescan Panel 2015 was used in this analysis, in which we were not able to detect the patterns of pricing and strategy of different brands, including whether they change over time or not. Besides these limitations, we contributed to the literature by pulling together an unconventional analysis regarding complex causal relationships among prices and quantities at various brand levels for nut products using cutting-edge machine learning algorithms.

Tables

Table 1. Descriptive Statistics of Prices and Quantities of Top 10 Brands of Nuts Products

	Brands	Mean	Std. Dev.	Min	Max
Prices ($/ounce)	Brand1[3]	0.33	0.01	0.31	0.35
	Brand2	0.28	0.02	0.23	0.31
	Brand3	0.61	0.03	0.53	0.67
	Brand4	0.50	0.04	0.42	0.58
	Brand5	0.54	0.06	0.40	0.67
	Brand6	0.60	0.04	0.50	0.70
	Brand7	0.10	0.00	0.09	0.11
	Brand8	0.60	0.03	0.53	0.66
	Brand9	0.25	0.02	0.23	0.30
	Brand10	0.41	0.01	0.39	0.43
Quantities (ounces)	Brand1	49500.50	7237.02	15690.90	69685.79
	Brand2	27458.75	6500.23	8380.75	42493.90
	Brand3	4922.14	1607.28	1874.05	10948.80
	Brand4	4516.49	1474.31	908.38	7323.88
	Brand5	3276.33	1923.49	1443.25	8686.75
	Brand6	2350.94	1460.55	842.00	7066.00
	Brand7	7535.47	1369.92	2907.96	11519.90
	Brand8	1189.34	343.90	313.25	1862.75
	Brand9	1604.72	435.71	582.25	2410.25
	Brand10	899.62	396.75	288.00	2192.00

Source: Nielsen Homescan Panel 2015, and calculations by authors.

[3] Brand 5 is store brand in Nielsen.

Table 2. Correlations Matrix of Unit Prices of Top 10 Brands

	Brand1	Brand2	Brand3	Brand4	Brand5	Brand6	Brand7	Brand8	Brand9	Brand10
Brand1	1.00									
Brand2	0.42	1.00								
Brand3	-0.20	-0.01	1.00							
Brand4	0.32	0.43	-0.18	1.00						
Brand5	-0.16	-0.14	0.45	0.17	1.00					
Brand6	-0.31	-0.37	0.37	-0.19	0.66	1.00				
Brand7	-0.02	-0.11	0.27	-0.32	0.13	0.23	1.00			
Brand8	0.16	0.04	0.05	0.35	0.34	0.22	-0.09	1.00		
Brand9	0.13	-0.15	-0.34	-0.12	-0.33	-0.07	0.14	-0.11	1.00	
Brand10	0.21	0.16	-0.27	0.00	-0.45	-0.30	-0.13	0.10	0.10	1.00

Source: Nielsen Homescan Panel 2015, and calculations by authors.

Table 3. Correlations Matrix of Quantities of Top 10 Brands

	Brand1	Brand2	Brand3	Brand4	Brand5	Brand6	Brand7	Brand8	Brand9	Brand10
Brand1	1.00									
Brand2	0.72	1.00								
Brand3	0.71	0.70	1.00							
Brand4	0.32	0.35	0.19	1.00						
Brand5	0.61	0.47	0.65	-0.26	1.00					
Brand6	0.55	0.43	0.52	-0.39	0.92	1.00				
Brand7	0.64	0.44	0.30	0.44	0.10	0.04	1.00			
Brand8	0.39	0.30	0.26	0.75	-0.21	-0.36	0.52	1.00		
Brand9	0.14	0.14	-0.03	0.69	-0.45	-0.50	0.35	0.72	1.00	
Brand10	0.38	0.29	0.18	-0.33	0.61	0.66	0.12	-0.29	-0.37	1.00

Source: Nielsen Homescan Panel 2015, and calculations by authors.

Table 4. Correlations of Prices and Quantities of Top 10 Brands

	Brand1P	Brand2P	Brand3P	Brand4P	Brand5P	Brand6P	Brand7P	Brand8P	Brand9P	Brand10P
Brand1Q	0.23	-0.09	-0.20	0.01	-0.16	-0.18	-0.08	-0.02	0.25	0.05
Brand2Q	0.19	-0.48	-0.35	-0.03	-0.08	-0.06	-0.07	0.11	0.17	0.03
Brand3Q	0.23	-0.18	-0.64	0.05	-0.42	-0.26	-0.11	-0.06	0.36	0.27
Brand4Q	-0.20	-0.56	0.21	-0.81	-0.07	0.25	0.38	-0.17	0.12	-0.07
Brand5Q	0.49	0.27	-0.54	0.38	-0.48	-0.61	-0.28	-0.02	0.29	0.30
Brand6Q	0.60	0.38	-0.42	0.53	-0.23	-0.60	-0.30	0.12	0.16	0.22
Brand7Q	-0.08	-0.20	0.02	-0.17	0.08	0.22	-0.08	-0.09	0.16	-0.11
Brand8Q	-0.17	-0.45	0.12	-0.55	-0.08	0.25	0.34	-0.29	0.17	-0.19
Brand9Q	-0.17	-0.31	0.33	-0.56	0.16	0.44	0.40	-0.16	-0.15	-0.22
Brand10Q	0.44	0.20	-0.24	0.43	-0.07	-0.43	-0.21	-0.01	0.07	-0.06

Source: Nielsen Homescan Panel 2015, and calculations by authors.

Table 4. Model Statistics

	Figure 4	Figure 5	Figure 6	Figure 7	Figure 8	Figure 9
Degrees of Freedom	35	35	159	159	158	715
Chi-square Statistics	76.57	794.61	2423.68	2363.63	1.49E+13	9.92E+12
P Value	0.00	0.00	0.00	0.00	0.00	0.00
BIC Score	-62.39	655.65	1792.40	1732.35	1.49E+13	9.92E+12
CFI	0.93	0.94	0.99	0.99	-7.54E+07	-840087
RMSEA	0.15	0.65	0.52	0.52	42515.03	16492.85

Table 5. Edge Coefficient for Figure 7

From	To	Type	Value	p-value
Brand1Q	Brand3Q	Edge Coef.	0.16	0.00
Brand5Q	Brand1Q	Edge Coef.	2.07	0.00
Brand2P	Brand1P	Edge Coef.	0.08	0.11
Brand4Q	Brand7P	Edge Coef.	0.00	0.01
Brand5P	Brand10P	Edge Coef.	-0.07	0.00
Brand5Q	Brand1P	Edge Coef.	0.00	0.37
Brand6P	Brand2P	Edge Coef.	-0.13	0.02
Brand5Q	Brand6P	Edge Coef.	0.00	0.00
Brand5Q	Brand9Q	Edge Coef.	-0.07	0.00
Brand6Q	Brand10Q	Edge Coef.	0.18	0.00
Brand6Q	Brand5Q	Edge Coef.	1.13	0.00
Brand5P	Brand6P	Edge Coef.	0.56	0.00
Brand4P	Brand8P	Edge Coef.	0.22	0.02
Brand3Q	Brand3P	Edge Coef.	0.00	0.00
Brand2Q	Brand4Q	Edge Coef.	0.05	0.00
Brand3P	Brand9P	Edge Coef.	-0.16	0.01
Brand5P	Brand8P	Edge Coef.	0.14	0.03
Brand4P	Brand2P	Edge Coef.	0.15	0.00
Brand5P	Brand5Q	Edge Coef.	-8353.58	0.00
Brand7Q	Brand1Q	Edge Coef.	3.09	0.00
Brand5P	Brand3P	Edge Coef.	0.11	0.06
Brand6Q	Brand1P	Edge Coef.	0.00	0.01
Brand8Q	Brand9Q	Edge Coef.	0.82	0.00
Brand6Q	Brand4P	Edge Coef.	0.00	0.00
Brand6Q	Brand6P	Edge Coef.	0.00	0.00
Brand6Q	Brand2Q	Edge Coef.	1.91	0.00
Brand1Q	Brand2Q	Edge Coef.	0.39	0.00
Brand4Q	Brand8Q	Edge Coef.	0.18	0.00
Brand2P	Brand2Q	Edge Coef.	-213813.49	0.00
Brand4P	Brand4Q	Edge Coef.	-25595.28	0.00
Brand7Q	Brand4Q	Edge Coef.	0.23	0.01

Source: Nielsen Homescan Panel 2015, calculations by authors.

Table 6. Edge Coefficient for Figure 8

From	To	Type	Value	p-value
Brand7Q	Brand1Q	Edge Coef.	1.07	0.01
Brand1Q	Brand3Q	Edge Coef.	6.92	0.00
Brand6Q	Brand8Q	Edge Coef.	0.90	0.00
Brand5P	Brand10P	Edge Coef.	0.93	0.00
Brand5P	Brand6P	Edge Coef.	1.81	0.00
Brand5Q	Brand9Q	Edge Coef.	1.04	0.00
Brand5Q	Brand6P	Edge Coef.	0.75	0.00
Brand5Q	Brand1Q	Edge Coef.	1.44	0.09
Brand2Q	Brand3Q	Edge Coef.	3.18	0.00
Brand3Q	Brand3P	Edge Coef.	2.14	0.00
Brand7Q	Brand8Q	Edge Coef.	1.00	0.00
Brand4Q	Brand8Q	Edge Coef.	1.24	0.00
Brand4P	Brand8P	Edge Coef.	0.09	0.33
Brand6Q	Brand5Q	Edge Coef.	0.66	0.00
Brand1Q	Brand2Q	Edge Coef.	2.30	0.00
Brand6Q	Brand1P	Edge Coef.	0.94	0.00
Brand6Q	Brand2P	Edge Coef.	0.75	0.00
Brand4P	Brand4Q	Edge Coef.	1.60	1.00
Brand5Q	Brand3P	Edge Coef.	1.08	0.00
Brand5P	Brand9P	Edge Coef.	0.77	0.00
Brand9Q	Brand7P	Edge Coef.	1.00	0.00
Brand6Q	Brand1Q	Edge Coef.	1.28	0.21
Brand5Q	Brand3Q	Edge Coef.	-2.18	0.00
Brand3Q	Brand9P	Edge Coef.	0.59	0.00
Brand3P	Brand1Q	Edge Coef.	2.00	1.00
Brand6Q	Brand10Q	Edge Coef.	6230.57	0.00
Brand8Q	Brand9Q	Edge Coef.	-0.67	0.00
Brand5P	Brand8P	Edge Coef.	1.10	0.00
Brand4P	Brand8Q	Edge Coef.	-6.55	1.00
Brand2P	Brand2Q	Edge Coef.	-0.09	1.00
Brand9Q	Brand4Q	Edge Coef.	1.39	0.00
Brand6Q	Brand4P	Edge Coef.	0.13	0.00

Source: Nielsen Homescan Panel 2015, calculations by authors.

Table 7. Edge Coefficients for Figure 9

From	To	Type	Value	p-value	From	To	Type	Value	p-value
Brand3Q	Brand1Q	Edge Coef.	113.82	0.00	Brand2P	Brand2P(t-1)	Edge Coef.	0.24	0.02
Brand6Q	Brand5Q	Edge Coef.	-6.91	0.00	Brand8Q(t-1)	Brand1Q(t-1)	Edge Coef.	-0.97	0.58
Brand4P(t-1)	Brand4Q(t-1)	Edge Coef.	33750.27	0.00	Brand4P(t-1)	Brand4Q	Edge Coef.	-1.76	1.00
Brand6P	Brand9P	Edge Coef.	-0.27	0.00	Brand5Q	Brand6P(t-1)	Edge Coef.	0.70	0.00
Brand2P(t-1)	Brand2Q(t-1)	Edge Coef.	-75365.67	0.01	Brand2P	Brand7Q(t-1)	Edge Coef.	8.78	1.00
Brand1Q(t-1)	Brand7Q(t-1)	Edge Coef.	-0.41	0.00	Brand10Q(t-1)	Brand2Q	Edge Coef.	-112873.50	0.00
Brand5P(t-1)	Brand10P	Edge Coef.	-0.42	0.00	Brand6Q(t-1)	Brand2Q(t-1)	Edge Coef.	-9012.11	0.00
Brand5P(t-1)	Brand9P(t-1)	Edge Coef.	0.41	0.00	Brand5Q(t-1)	Brand6P(t-1)	Edge Coef.	0.92	0.00
Brand5P(t-1)	Brand5P	Edge Coef.	-0.09	0.14	Brand7Q(t-1)	Brand8Q(t-1)	Edge Coef.	-0.41	0.00
Brand8Q	Brand9Q	Edge Coef.	-2332.12	0.00	Brand5P(t-1)	Brand6P	Edge Coef.	-0.40	0.00
Brand1Q(t-1)	Brand2Q(t-1)	Edge Coef.	1473.68	0.00	Brand5P	Brand10P(t-1)	Edge Coef.	-0.19	0.00
Brand5Q(t-1)	Brand5Q	Edge Coef.	-1.02	0.00	Brand8Q(t-1)	Brand4Q(t-1)	Edge Coef.	-1179.70	0.00
Brand7Q	Brand8Q	Edge Coef.	-0.05	0.08	Brand6Q(t-1)	Brand1P(t-1)	Edge Coef.	0.03	0.00
Brand6Q(t-1)	Brand1Q(t-1)	Edge Coef.	1.15	0.01	Brand3Q(t-1)	Brand3Q	Edge Coef.	0.37	0.00
Brand4Q	Brand8Q(t-1)	Edge Coef.	-4.46	0.00	Brand8Q(t-1)	Brand9Q(t-1)	Edge Coef.	1392.24	0.00
Brand6Q	Brand9Q	Edge Coef.	23443.42	0.00	Brand10Q(t-1)	Brand10Q	Edge Coef.	0.05	0.60
Brand3Q	Brand2Q	Edge Coef.	5320.14	0.00	Brand4P(t-1)	Brand1P	Edge Coef.	-0.14	0.00
Brand9Q	Brand9Q(t-1)	Edge Coef.	-0.61	0.00	Brand6Q	Brand1P	Edge Coef.	0.99	0.00
Brand4P	Brand4Q	Edge Coef.	-1.84	1.00	Brand4Q	Brand8Q	Edge Coef.	0.40	0.00
Brand3P(t-1)	Brand3Q(t-1)	Edge Coef.	3.08	1.00	Brand2P	Brand8Q(t-1)	Edge Coef.	3.38	1.00
Brand1Q(t-1)	Brand3Q(t-1)	Edge Coef.	0.86	0.00	Brand5P(t-1)	Brand6P(t-1)	Edge Coef.	-0.70	0.00
Brand7P(t-1)	Brand9Q	Edge Coef.	60275.97	0.00	Brand2P	Brand2Q	Edge Coef.	-87413.51	0.00
Brand3Q	Brand3P	Edge Coef.	-0.26	0.00	Brand6Q	Brand10Q(t-1)	Edge Coef.	-5.09	0.00
Brand6Q	Brand6Q(t-1)	Edge Coef.	-7.15	0.00	Brand6P	Brand9Q(t-1)	Edge Coef.	-4906.74	0.00
Brand1Q	Brand2Q	Edge Coef.	-104.56	0.00	Brand5P	Brand6P	Edge Coef.	-0.12	0.37
Brand7P	Brand9Q(t-1)	Edge Coef.	-21513.18	0.04	Brand8Q	Brand1Q	Edge Coef.	-737.18	0.00
Brand2P(t-1)	Brand4Q(t-1)	Edge Coef.	-6610.75	0.24	Brand6Q	Brand6P	Edge Coef.	1.19	0.00
Brand5P(t-1)	Brand5Q(t-1)	Edge Coef.	0.92	1.00	Brand5Q(t-1)	Brand3P(t-1)	Edge Coef.	-0.50	0.00
Brand4P	Brand8P	Edge Coef.	0.21	0.03	Brand6Q(t-1)	Brand5Q(t-1)	Edge Coef.	-0.69	0.00

Brand2P	Brand1P	Edge Coef.	0.55	0.00	Brand5Q	Brand1Q	Edge Coef.	-67.99	0.00
Brand5P(t-1)	Brand9P	Edge Coef.	-0.90	0.00	Brand8Q	Brand8P(t-1)	Edge Coef.	-0.32	0.00
Brand7Q	Brand1Q	Edge Coef.	-10.49	0.00	Brand10Q	Brand7P(t-1)	Edge Coef.	0.09	0.00
Brand5P(t-1)	Brand5Q	Edge Coef.	-0.24	1.00					

Source: Nielsen Homescan 2015, and calculations by authors.

Figures

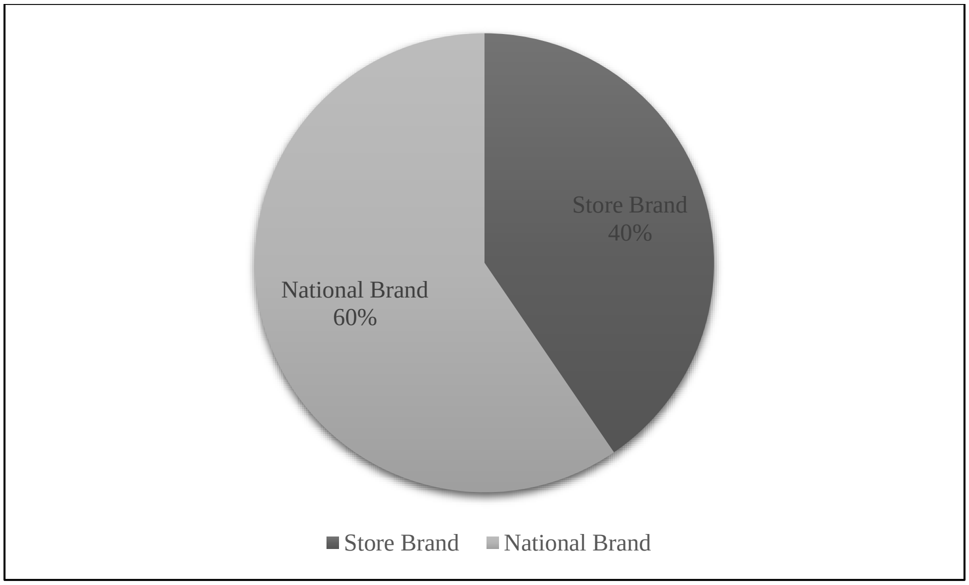

Figure 1. Market Shares of Store Brand and National Brand of Nuts

Source: Nielsen Homescan Panel 2015

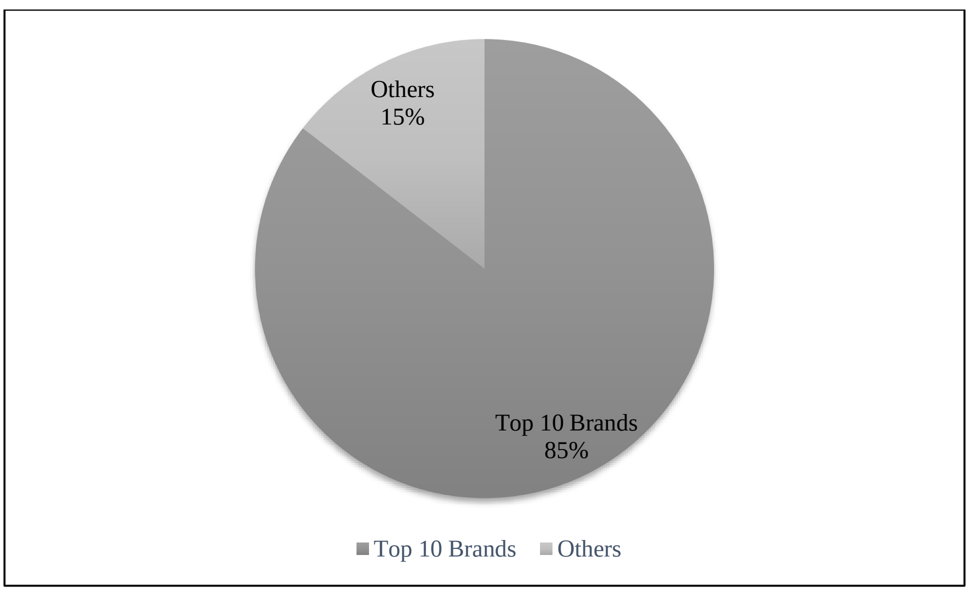

Figure 2. Market Shares of Top 10 Brands and Other Brands

Source: Nielsen Homescan Panel 2015

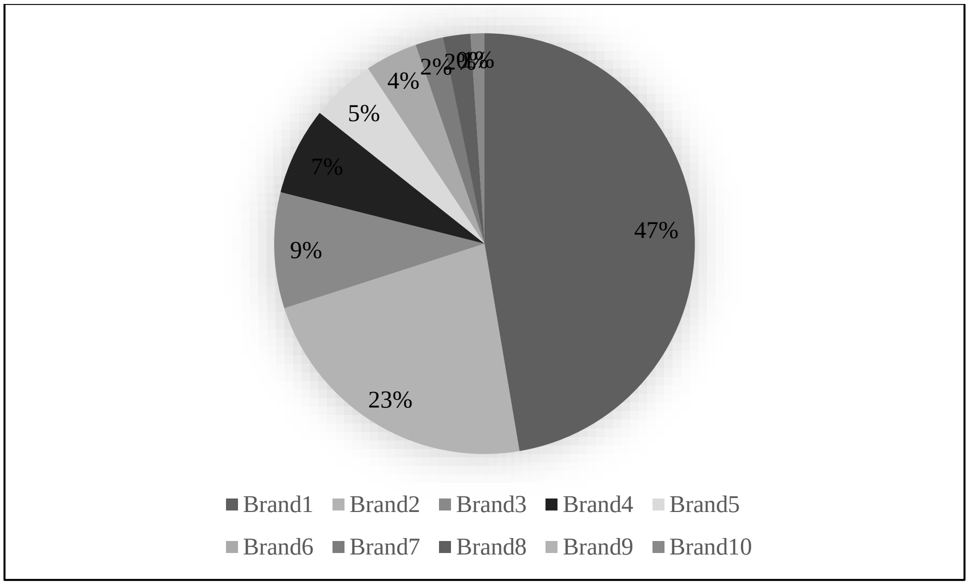

Figure 3. Market Shares of Store Brand and National Brand of Nuts

Source: Nielsen Homescan Panel 2015

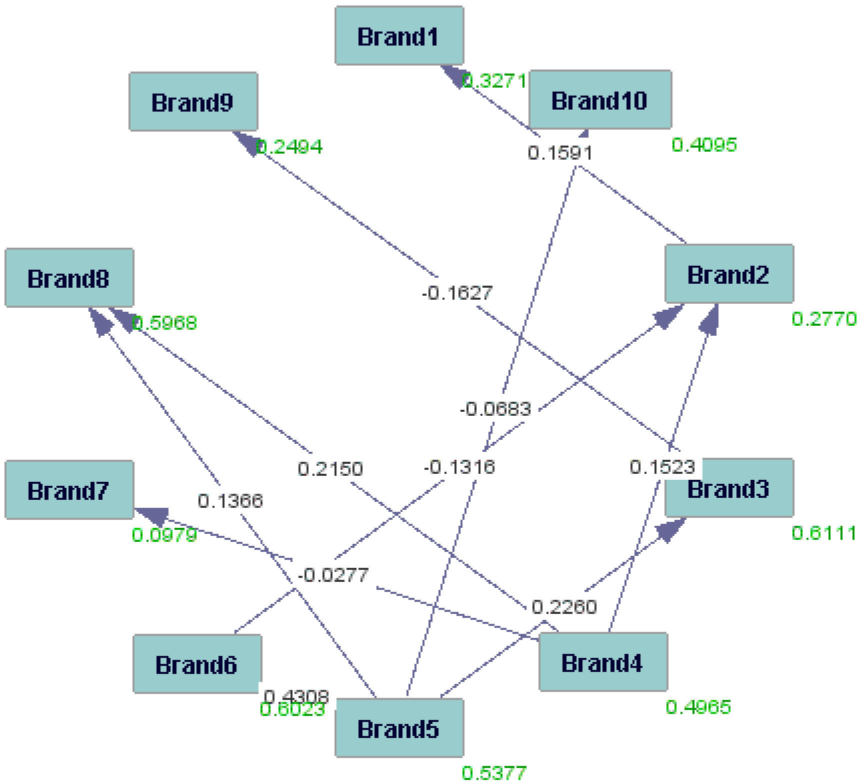

Figure 4. Directed Acyclic Graph of Unit Prices of Top 10 Brands in Current Week, No Prior Knowledge Assumed

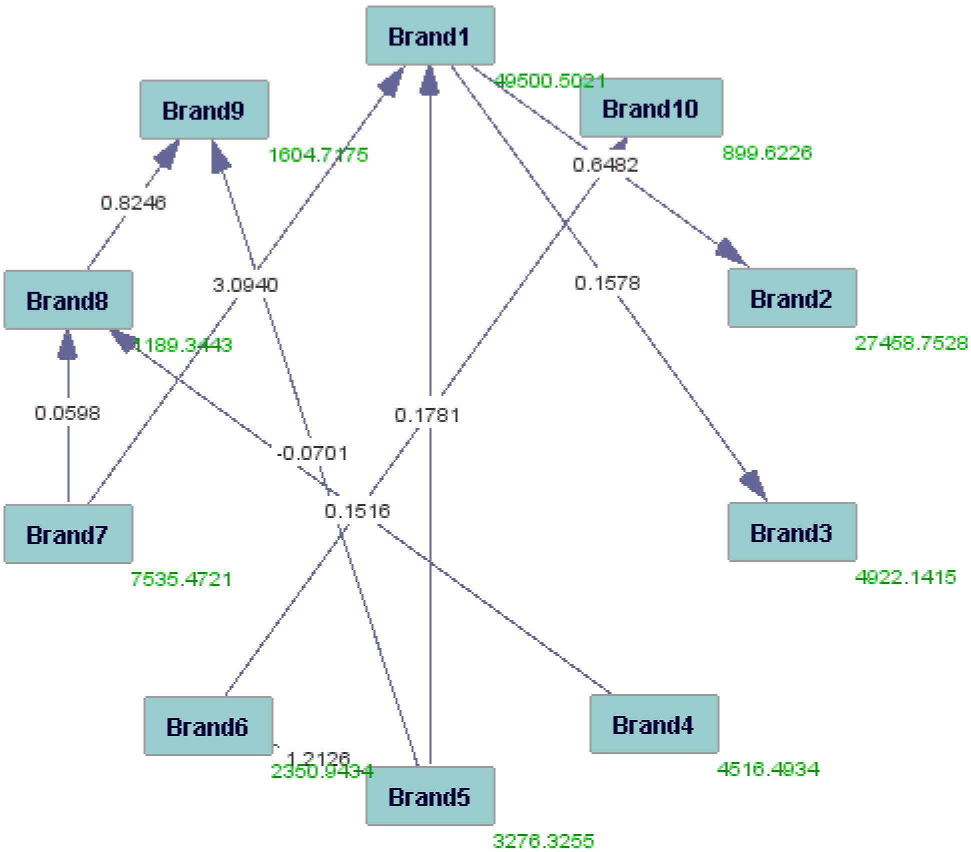

Figure 5. Directed Acyclic Graph of Quantities of Top 10 Brands in Current Week, No Prior Knowledge Assumed

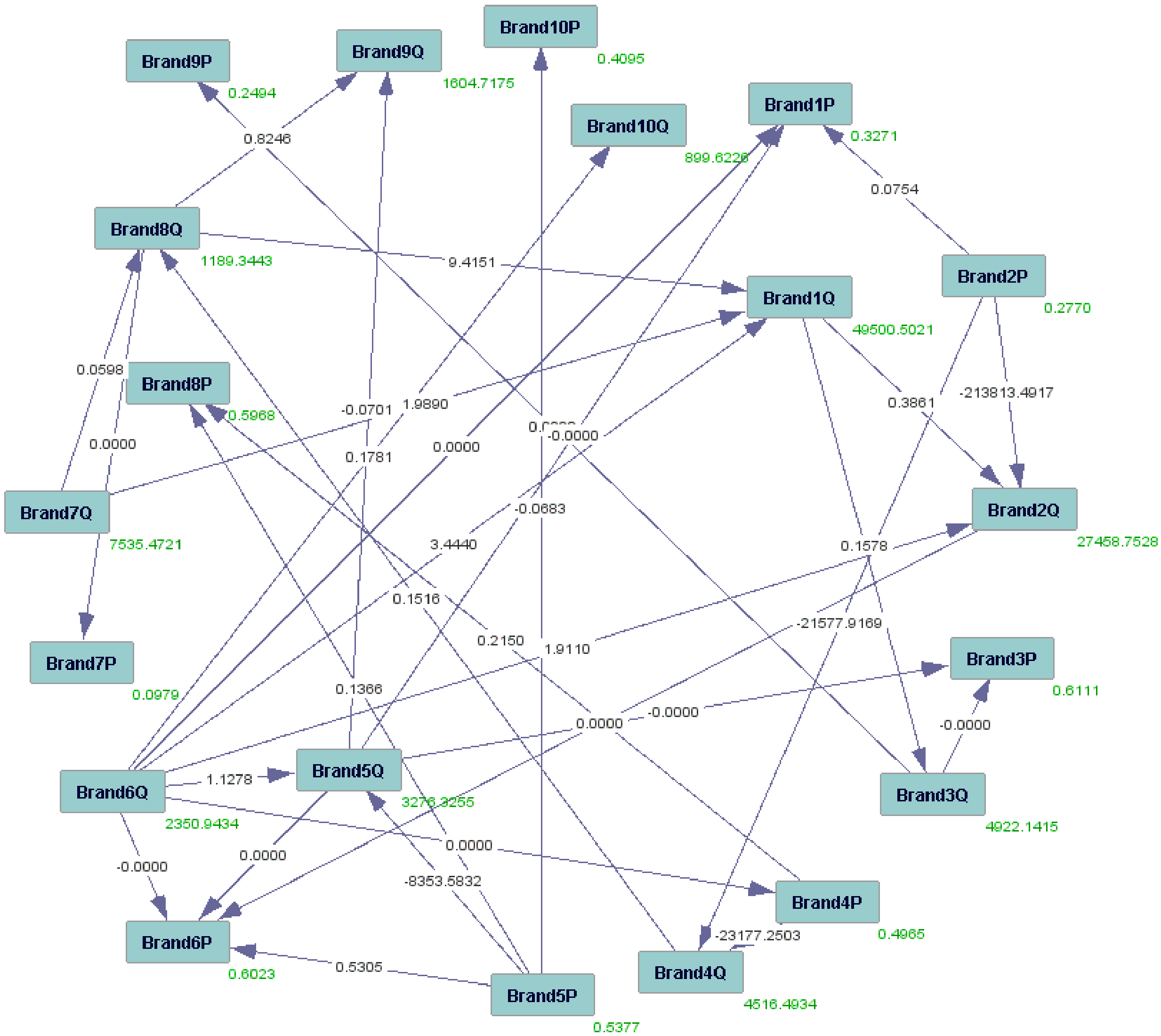

Figure 6. Directed Acyclic Graph of Unit Prices and Quantities of Top 10 Brands in Current Week, No Prior Knowledge Assumed

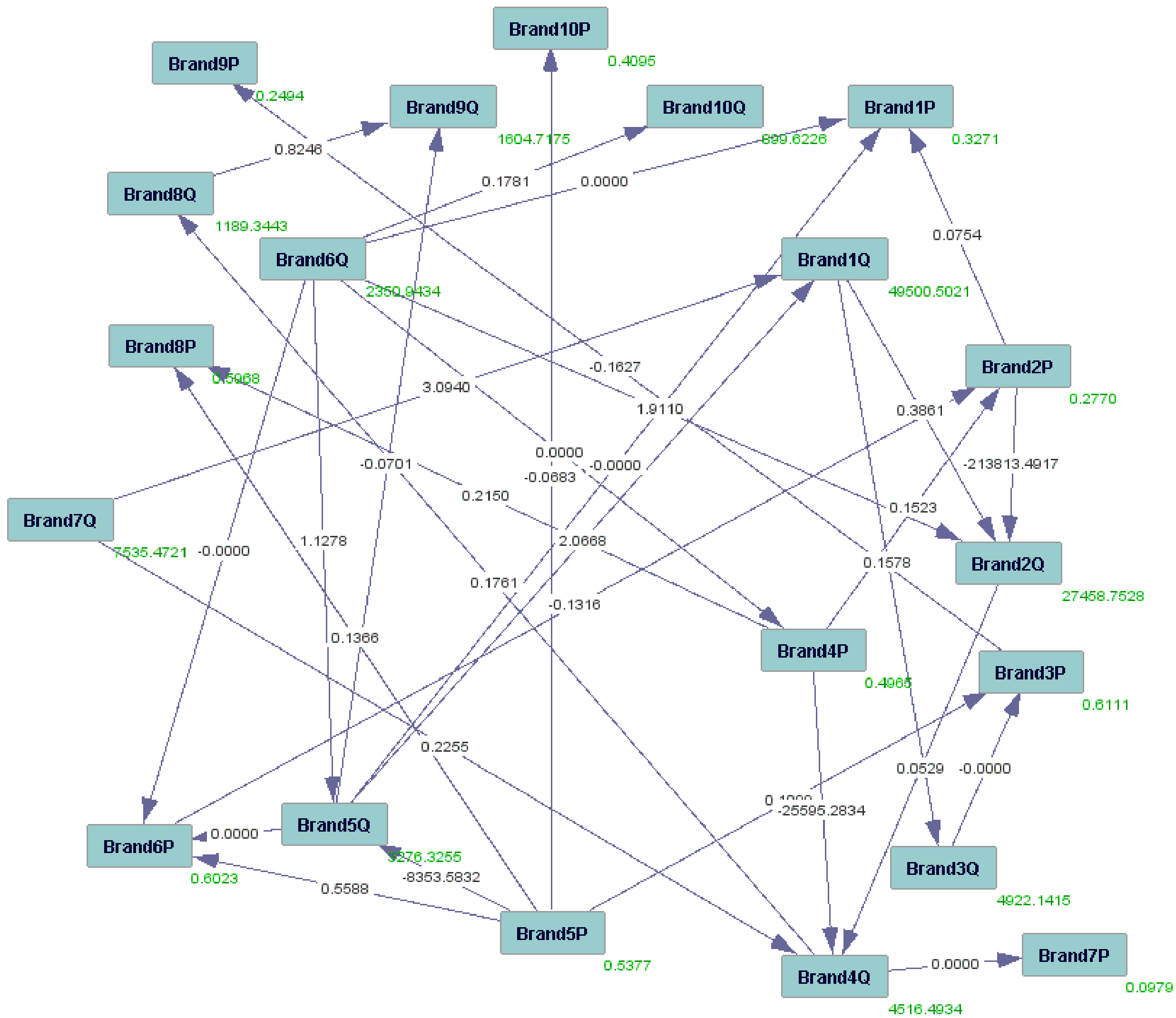

Figure 7. Directed Acyclic Graph of Unit Prices and Quantities of Top 10 Brands in Current Week with Imposed Knowledge (Quantity responds to Price)

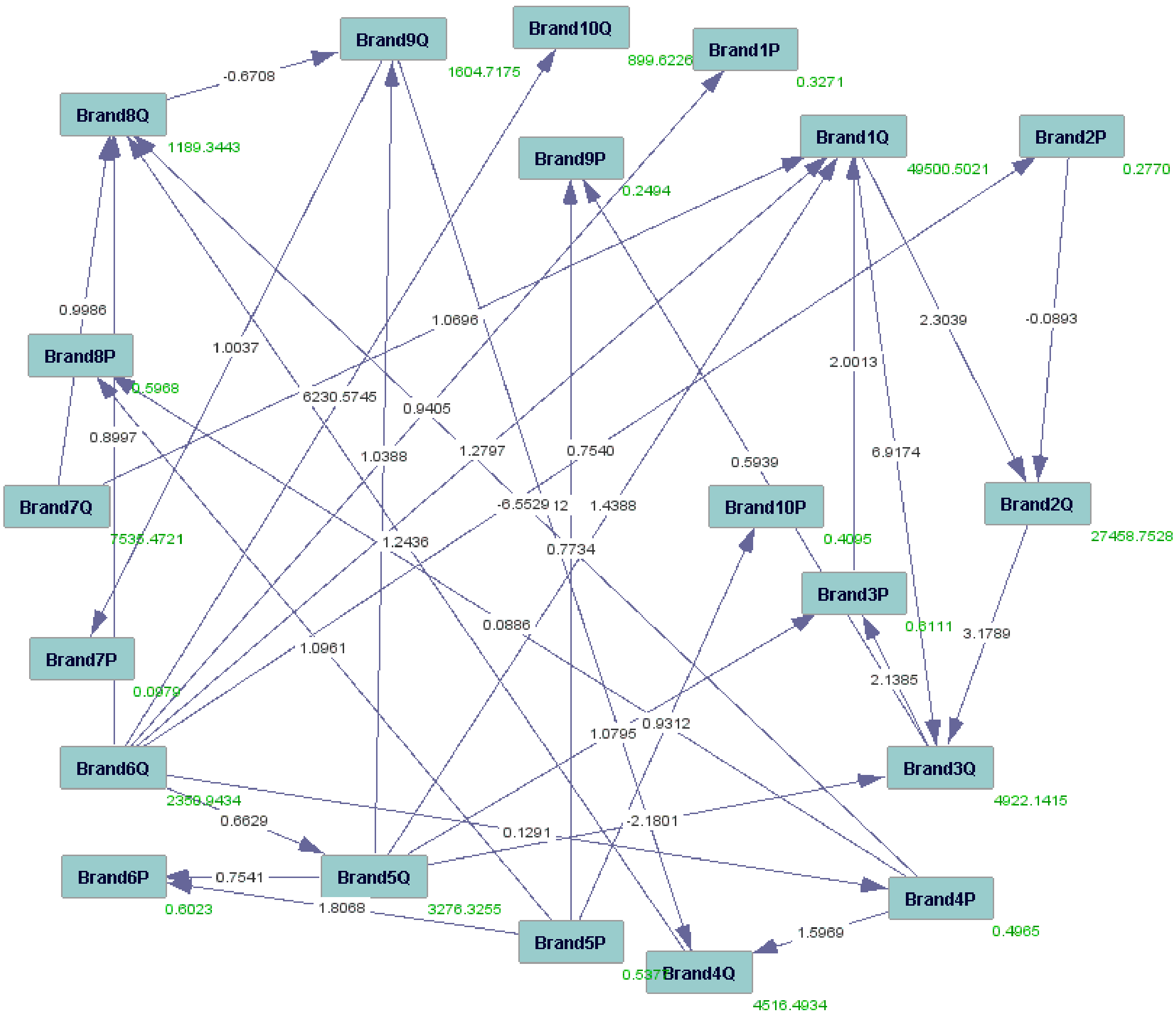

Figure 8. Directed Acyclic Graph of Unit Prices and Quantities of Top 10 Brands in Current Week with Imposed Knowledge (Price responds to Quantities)

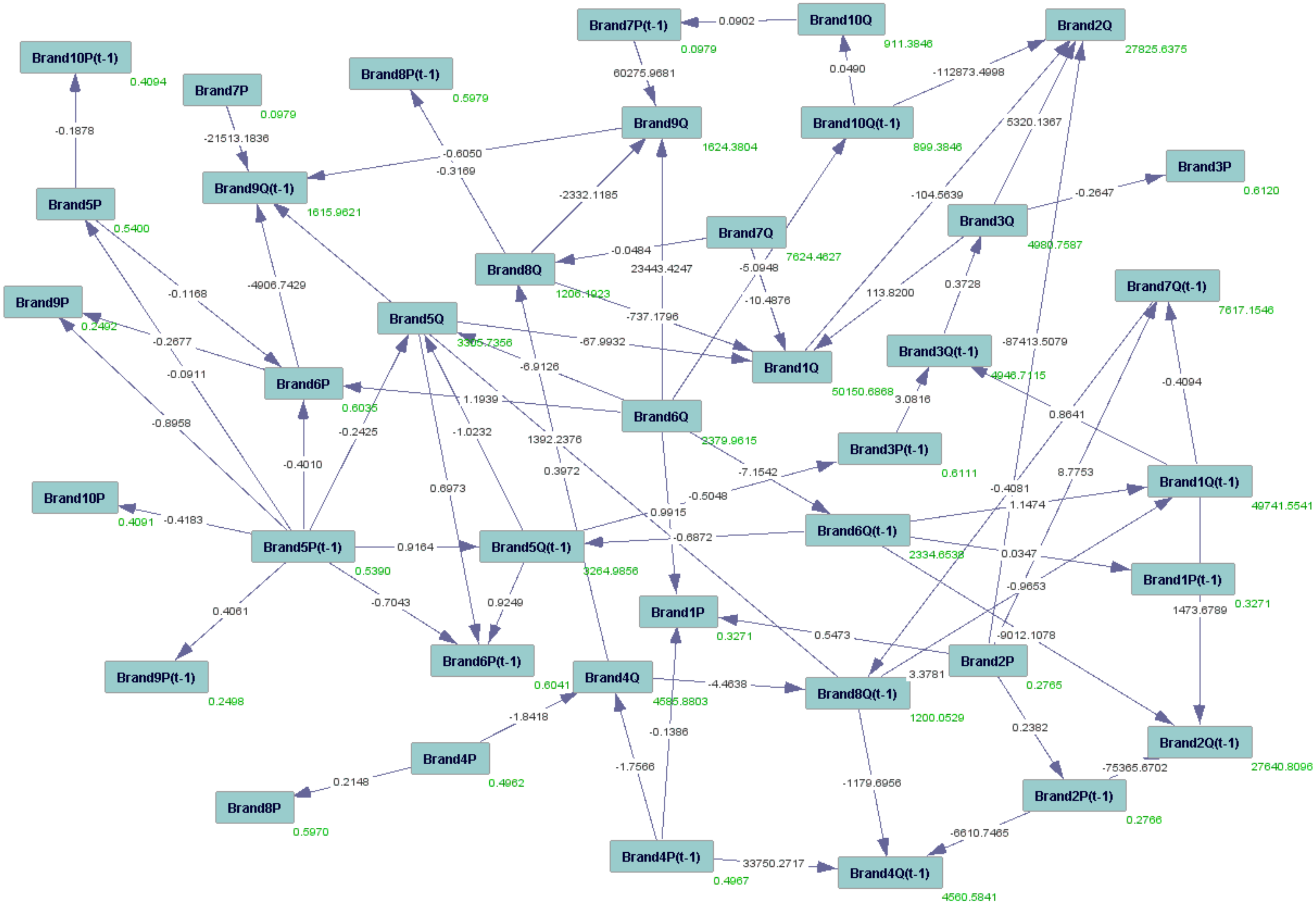

Figure 9. Dynamic Relationship between Prices and Quantity with their Lag One Period

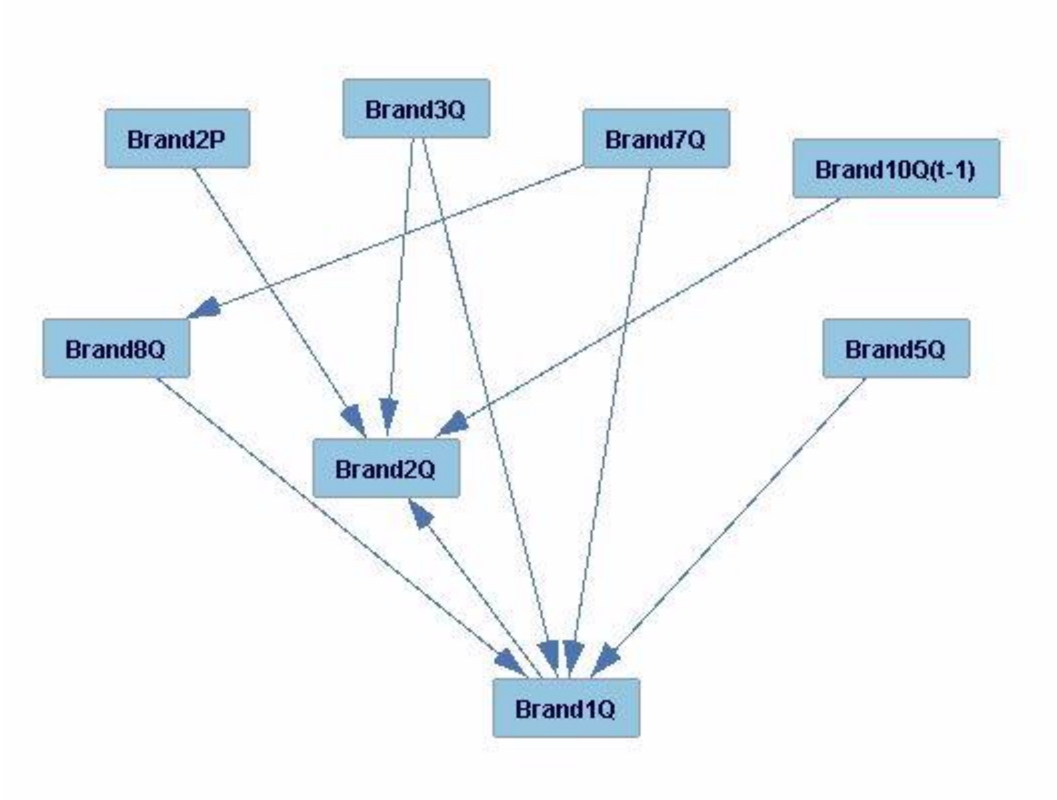

Figure 10. Markov Blankets for Quantity of Store Brand

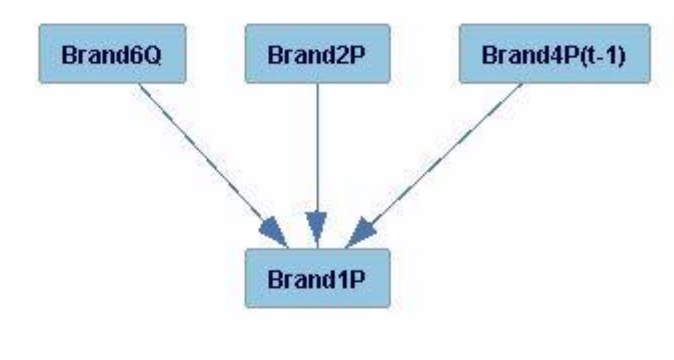

Figure 11. Markov Blankets for Unit Price of Store Brand

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