USDA Approved 01-07-2019

Price Elasticities of Demand for Fresh Hass Avocados in the United States

Concepts, Estimation, and Applications

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Executive Summary

This study evaluates price elasticities of demand for fresh Hass avocados in various dimensions of time period, location, geographic market aggregation, and stage of the market chain (retail and shipper/wholesale). Price elasticity of demand measures in percentage terms how sales of a product respond to a one percent increase in its price. Our primary focus is on the price elasticity of demand for fresh Hass avocados at retail. Analysis is based on retail scanner data assembled by IRI for the time period 2013 – 17 and provided for this study by the Hass Avocado Board.

Estimates of weekly demand for 45 metropolitan and local regional markets revealed that demand in most but not all the markets is somewhat elastic in that the percent change in quantity exceeds the percent change in price that precipitated it. The estimated price elasticities were estimated with high statistical precision and range from a low of -0.71 in Boise, Idaho to a high of -1.64 in Pittsburgh, so the models predict consumers in Pittsburgh are twice as responsive to price of fresh avocado as are consumers in Boise. Most of the metropolitan-area weekly elasticity estimates are quite similar, with 80% falling in the range of -1.5 to -1.0. We also estimated the price elasticity of demand for these same areas over a time interval of one month and found that these demands were consistently less elastic than weekly demands. Most are price inelastic, meaning that the estimated elasticities are less than 1.0 in absolute value. The difference between weekly and monthly values likely reflects a rebound effect wherein consumers accelerate weekly purchases to take advantage of low sale prices, but then reduce purchases in the following weeks when fresh avocados return to full price.

Weekly and monthly models were also estimated for eight U.S. regions based on IRI definitions. The elasticities at the regional level are broadly comparable to those estimated for metropolitan areas. Retail demand is mildly price elastic (elasticities greater than 1.0 in absolute value) in six of the eight regions and slightly inelastic (less than 1.0) in California and the South-Central region. The most price elastic region is the Southeast, with an estimate of -1.44, followed by the Great Lakes, with an estimate of -1.36. Regional demand is also less responsive to price changes over a monthly time interval. All eight of the regions show inelastic demands when viewed over monthly horizons, with California and South Central once again being the regions that are most unresponsive to price.

Finally, estimation was also conducted for the U.S. market as a whole and was evaluated at both the retail and shipper levels of the market based upon monthly data for 2013 – 17. We estimate that aggregate retail demand is slightly inelastic to price, with point estimates around -0.89. Demand, however, is much more inelastic at the shipper level, with point estimates ranging from -0.19 to -0.24, depending on model specification. Thus, a price decrease at the shipper level of 10% is predicted to only expand sales by about 2%. Conversely, an increase in shipments of 2% is predicted to decrease the shipper prices by 10%

These results have wide applicability to people producing and selling fresh Hass avocados for the U.S. market. They provide insights as to (i) the benefits of holding price promotions for fresh avocados, (ii) where additional shipments can be targeted with minimum impact on prices, (iii) which markets are best targeted for promotion expenditures, and (iv) the likely price implications of supply disruptions to the U.S. market due to harvest issues or other factors.

Table of Contents

1 Introduction 1

2 Conceptual Background and Methodology 3

3 Data and Estimation Results 8

3.1 Estimation Results and Discussion 11

3.2 Price Elasticities by Region 18

3.3 Retail Price Elasticities at the National Level 22

3.4 Shipper Price Elasticities at the National Level 22

4 Applications 26

5 Conclusion 29

List of Tables

Table 1. Statistics by Market Area 9

Table 2. Market-Level Elasticities and Confidence Intervals, Weekly 11

Table 3. Market-Level Elasticities and Confidence Intervals, Monthly 15

Table 4. Regional Elasticities and Confidence Intervals, Weekly 19

Table 5. Regional Price Elasticity Estimates and Confidence Intervals 20

Table 6. National Model Estimation Results 23

List of Figures

Figure 1. Linear and Log Linear Demand Functions 7

Figure 2. Market Price Elasticity Point Estimates and 95% Confidence Intervals, Weekly 13

Figure 3. Market Price Elasticity Point Estimates and 95% Confidence Intervals, Monthly 17

Figure 4. Regional Elasticity Point Estimates and 95% Confidence Intervals, Weekly 19

Figure 5. Regional Price Elasticity Point Estimates and 95% Confidence Intervals, Monthly 21

Figure 6. The Relationship Between Demands at the Retail and Shipper Levels 25

1 Introduction

Price elasticity of demand is a widely used concept in economics and marketing. It measures the demand response to a change in price. In particular, for a good X, let Q_X denote the quantity of good X purchased and utilized at price P_X. Then price elasticity of demand for good X can be written as

$$\eta_X = \frac{\%\Delta Q_X}{\%\Delta P_X} = \frac{\Delta Q_X / Q_X}{\Delta P_X / P_X} = \frac{\Delta Q_X}{\Delta P_X}\frac{P_X}{\Delta Q_X}.$$ [1]

In other words, the price elasticity of demand answers the question, “what percentage change in quantity demanded would result from a small (1%) percentage increase in its price?” The virtue of measuring response of sales and consumption to a change in price in percentage form is that the elasticity is a pure number; it does not depend on the units the analyst is using to measure quantities of prices.

Apart from exceptional circumstances, a price elasticity of demand is always a negative number. This merely reflects the “law of demand;” demand curves slope downward, so higher prices imply less sales and consumption. A demand is said to be *elastic* if $|\eta_X| > 1$, i.e., if the percent change in quantity exceeds the percent change in price that precipitated it. In other words, an elastic demand is relatively responsive to a change in price. Conversely, demand is *inelastic* or relatively unresponsive to price if $|\eta_X| < 1$, i.e., the percent change in quantity is less than the percent change in price.

Although price elasticity of demand is a very useful concept for business managers, market analysts, and policymakers, this brief introduction should raise more questions than it answers. What is included in good X? Is it a particular brand or variety of a product, or is it a commodity aggregate, with individual brands and varieties lumped together in some manner?

[1] For those familiar with basic calculus, the elasticity can be written in calculus notation as $\eta_X = \frac{\partial Q_X}{\partial P_X}\frac{P_X}{Q_X}$.

Over what time period are we measuring the response of sales and consumption to a change in price—weekly, monthly, seasonally, yearly, etc.? The resulting elasticity estimate will differ depending upon how the product and time frame are defined. For example, individual brands or varieties of a product can be expected to have more elastic demands than the aggregate commodity because competing brands or varieties are substitutes for any single brand or variety, making such demands generally very responsive to price changes. Considering the time dimension, demands may become more responsive to price or more elastic over longer time periods as buyers have more opportunities to adjust their spending patterns in response to a price change.

In addition, whose demand are we measuring – individual consumers, or consumers aggregated across locations such as cities, states, regions, or countries? Or are we talking about the demand of market intermediaries for a product? For example, in the context of fresh avocados, shippers demand avocados from growers, and retailers and food-service establishments demand avocados from shippers. These demands of market intermediaries are known as *derived demands* because they are based on, and closely related to, the demand of the ultimate consumers.

The answer to these questions will depend upon the information a decision maker needs, but it is important to understand that the value of the price elasticity of demand will depend on (i) how the analyst defines the product, (ii) whose demand she is studying (final consumers or market intermediaries), (iii) to what geographic levels the demands are being aggregated, and (iv) the time interval over which we are measuring prices and sales/consumption.

In this report we provide estimates of final consumers' demands for fresh Hass avocados in the U.S. market, focusing on the response of demand to price at retail. Based on the available data, we will report price elasticity estimates at multiple levels of geographic aggregation—individual metropolitan areas, regions, and the U.S. as a whole—and over alternative time periods. We also estimate a derived demand of retailers for fresh avocados. This demand represents the demand facing shippers who sell to U.S. retailers.

2 Conceptual Background and Methodology

Our study is simplified by the fact that almost all fresh avocados sold in the U.S. are Hass avocados. Thus, challenges that would be present for other commodities in terms of aggregating (or not) across different varieties of a commodity are avoided for avocados and we can focus directly on analyzing demand for fresh Hass avocados.[2]

Price is only one factor impacting demand for a product. It is an especially important factor because it is often under the control or influence of market participants, either directly for sellers who specify prices for their products, or indirectly for sellers who determine quantities to place on the market, which then contribute to determining prices through the workings of the marketplace. Even though our direct interest here is on the relationship between price and sales, we must account for the other factors that influence demand in order to obtain an unbiased estimate of the effect of price on demand.

Our work for this study proceeds in a fashion analogous to the process undertaken by the same authors in the evaluation of promotion programs conducted under the auspices of the Hass Avocado Board (Ambrozek, Saitone, and Sexton 2018). We must first specify a conceptual

[2] We should note that fresh Hass avocados sold in the U.S. originate in multiple locations, most notably Mexico, California, Peru, and Chile. Grower and shipper organizations from each location promote their avocados through the auspices of the Hass Avocado Board and attempt to create product differentiation based on country of origin. We describe and study these promotion programs in our companion report, Ambrozek, Saitone, and Sexton (2018). However, it is impossible to study whether demand elasticities differ by country of origin. Multiple growing locations are selling fresh Hass avocados in the U.S. at any time of the year, and the retail scanner data used for this study do not identify the country of origin.

model of consumer demand, and then convert that model into an econometric framework suitable for estimation with the available data. Thus, for a time period *t*, where *t* will denote either weeks or months in this study, and a market area *j,* where *j* will denote metropolitan areas, regions within the U.S., or the nation as a whole, we can specify a consumer demand function for fresh Hass avocados in general form as follows:

$$Q_{t,j} = f\left(P_{t,j} \middle| \boldsymbol{Z_{t,j}}\right),$$

where $Q_{t,j}$ denotes per capita retail sales of fresh Hass avocados at time *t* in market area *j*,[3] $P_{t,j}$ is price at time *t* in market *j*, and $\boldsymbol{Z_{t,j}}$ represents a vector of other factors that might influence fresh avocado sales at time *t* in market area *j*. In words the equation states that quantity of fresh avocados sold in market *j* at time *t* is a function of the price of fresh avocados in market area *j* at time *t*, given a set of values for other factors that impact demand and are contained in $\boldsymbol{Z_{t,j}}$.

The work we conducted for the Hass Avocado Board (HAB) promotion evaluation provides some immediate examples of what might be included in $\boldsymbol{Z_{t,j}}$—promotions directed to market *j* at time *t*, and possibly lagged values of price. Promotion expenditure was found to positively impact sales, and a one-period lag of price (P_{t-1}) was found to have a significant impact on current period sales in weekly demand models specified for the promotion evaluation study, with the economic rationale being that a high volume of purchases in week *t* when fresh avocados were on sale could be offset by reduced purchases in the following week when the product was no longer on sale.

Other factors known to impact demands for food products include consumers' incomes or purchasing power, prices of related goods, and measures of consumer demographics. For most

[3] Specifying demand in per capita form eliminates the need to deal with differences in market size based on population.

foods consumption in the U.S. rises (slowly) as consumer incomes rise. Impacts of market demographics depend on the commodity under investigation. For fresh avocados we would expect the Hispanic share of population in a market area to be positively correlated with avocado consumption, and we would expect a younger population to consume more avocados per capita because this population cohort has grown up during a time when fresh avocados have been widely available in the U.S.

These factors, while of overall interest in understanding the demand for fresh avocados in the U.S., are not of direct interest in this study. It is nonetheless important to control for impacts on demand of these factors lest our analysis be subject to what is known as omitted variable bias.[4] For example, City A may have a consistently higher per capita consumption of fresh avocados than city B because City A has a younger consumer demographic. Our strategy is to estimate separate econometric models for each market or region, in which case the constant or intercept term in the regression equation absorbs any variation in demand caused by demographics or other time-invariant factors that do not change over our sample period.[5]

Fresh Hass avocado consumption has a strong seasonal component, with per capita consumption being higher during summer months and lowest in October-December (Ambrozek, Saitone, and Sexton 2018). The econometric model can account for impacts of seasonality by introducing {0,1} indicator variables to denote observations for each month of the year, i.e., we would introduce 11 such variables (with exclusion of one month made necessary for statistical reasons) to capture seasonality in demand.[6] These indicator variables are known as *fixed effects*.

[4] Formally, an econometric model is subject to omitted variable bias if (a) important explanatory variables are excluded from a model and (b) those omitted variables are correlated with the variables that are included in the model.

[5] An equivalent step is to subtract average or mean per capita consumption in a city from each of its observations and then seek to explain deviations in consumption from the mean.

[6] Understanding the seasonality in demand for fresh Hass avocados can be interesting and important in its own right. Ambrozek, Saitone, and Sexton (2018) in their promotion evaluation study report estimates of month-by-month

Finally, we need to control for variables that change systematically over time in our data sample and impact all cities or regions in a similar way. Good examples would be growth in Hispanic population share in the U.S. and growth in disposable income of U.S. consumers. Both factors would be expected to increase per capita demand for fresh avocados, and can be accounted for in the model at least partially through introduction of a fixed effects variable for each year included in the data set. Such fixed-effects variables will capture trends in demographics and income that impact all cities or regions in a data set in an equivalent way.

A final consideration is the functional form to choose for the demand relationship. Common choices are the linear form where we would specify the relationship between per capita consumption and price as $Q_{j,t} = \alpha + \beta P_{j,t}$ and the double log form where the variables are converted to their natural logarithms and the relationship between consumption and price is multiplicative in the levels of the data, but linear in the logs: $lnQ_{j,t} = a + blnP_{j,t}$.[7] Figure 1 depicts the linear (in blue) and log linear (in red) representations of demand, each drawn in relation to a base price and quantity $(P_{j,t}^1, Q_t^1)$.

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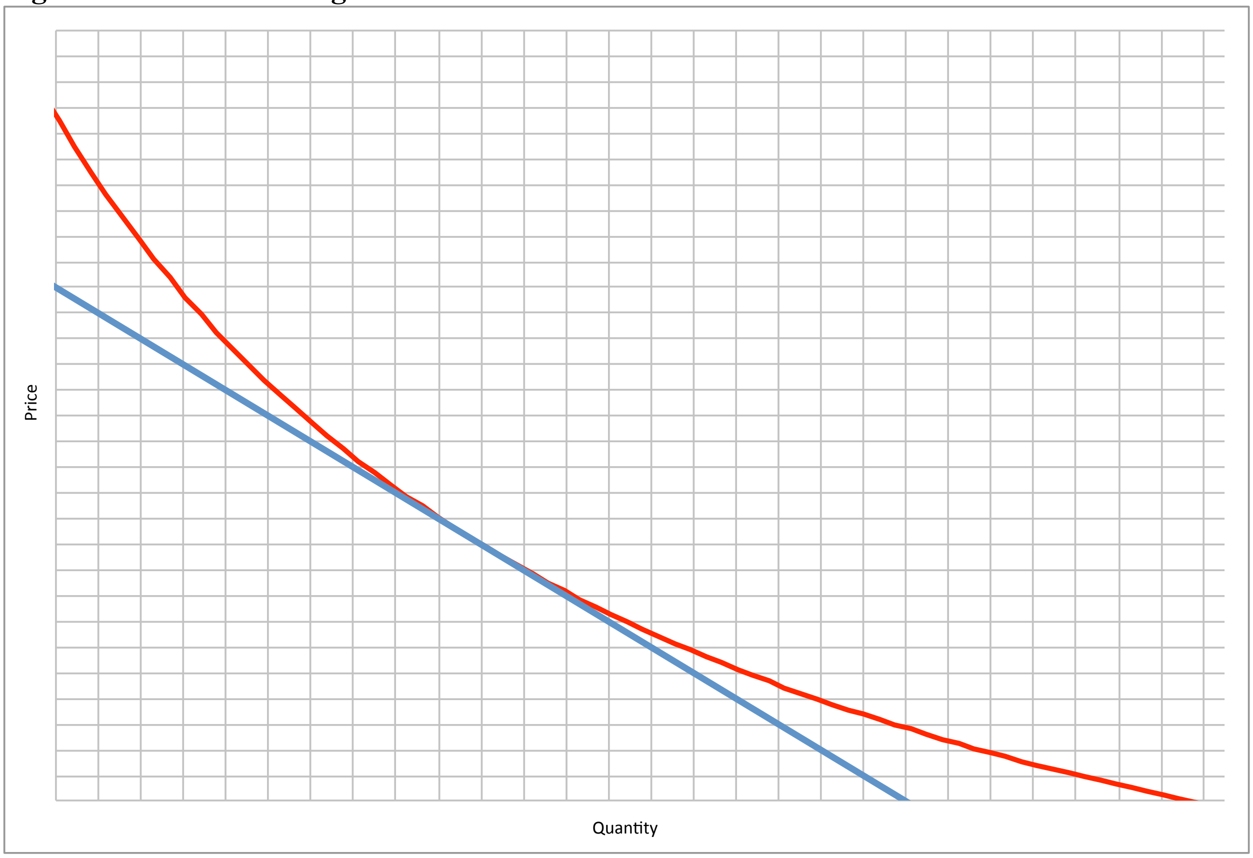
seasonality. These estimates account for variations in price and promotion expenditure that may also vary by month and season. Thus, they represent a truer representation of seasonality than one would obtain, for example, from simply comparing total fresh avocado sales across the months.

[7] In these simple representations of the demand relationship, all other factors that affect demand are implicitly subsumed within the intercept terms, α and a.

Figure 1. Linear and Log Linear Demand Functions



In conducting the HAB promotion evaluation study the authors found that the double log model provided a better representation of the demand relationship for fresh avocados compared to the linear model. This model has two other advantages over the linear form. First, elasticities obtained from double-log models are the estimated coefficients, and the standard errors associated with the estimated coefficients can be used to construct confidence bounds for the elasticity estimates. Second, the elasticity of demand in a double-log model is constant at all points along the demand curve, meaning that interpretation of the effect of price on quantity demanded will not change depending on the levels of price or quantity. We estimated both linear and double log models for all specifications of the demand relationship in this study as a check on robustness of results to the choice of functional form, but given preference for the constant elasticity form, we focus discussion on results from the double log model.

3 Data and Estimation Results

The retail sales data used for this analysis are based on scanner data collected by Information Resources, Inc. (IRI) and provided by the Hass Avocado Board. The data include total weekly retail sales in value and volume for fresh Hass avocados (aggregated across all relevant PLU codes) in 45 distinct local market areas and eight regions (53 cross sectional observations in total) for the five years spanning 2013 – 17.[8] These data represent an aggregation of retail outlets that includes the following channels: grocery, mass merchandisers, club stores, drugstores, dollar outlets and military commissaries. An average price or unit value is computed in each market and each week by dividing sales value by the number of fresh Hass avocados sold. Population data for each market area on an annual basis were also available from IRI and were utilized to convert sales volume to a per capita basis in each market area. These weekly data were also aggregated to the monthly level to conduct analysis over a longer time horizon.

Table 1 provides summary data on the market areas included in the analysis, including population mean, mean and standard deviation of weekly per capita sales quantity of fresh Hass avocados, mean and standard deviation of average sales price (ASP) in cents, and mean and standard deviation of per capita retail sales value in cents. The eight regional markets defined by IRI are indicated in boldface type. The regional market to which each individual market belongs is indicated in parentheses next to the market name. Notable in the table is the price and per capita consumption variation across market areas. For example, weekly per capita consumption

[8] Most of these local markets represent metropolitan areas, although a few are localized regions and not metropolitan areas per se. In particular, North Texas/New Mexico, South Carolina, and Northern New England are included in the 45 market areas. See table 1 for a complete listing of the market areas included in the IRI scanner data.

ranges from a low of 0.04 in Pittsburgh to a high of 0.20 in Phoenix/Tucson. Similarly, the standard deviations indicated in brackets for per capita consumption and price for each market area are relatively large compared to the mean values, reflecting changes in price and consumption within market areas over the course of a year.[9] This substantial variation in price and consumption in the data provides a good opportunity to identify the impacts of price on per capita sales.

Table 1. Statistics by Market Area

Market	Mean	Mean [SD]	Mean [SD]	Mean [SD]
	Population (millions)	***Per capita avocados sold***	***ASP (¢ per avocado)***	***Per capita retail sales value (¢)***
Albany (NE)	1.13	0.06 [0.03]	126 [18]	7.97 [3.84]
Atlanta (SE)	5.16	0.08 [0.02]	116 [17]	9.57 [2.29]
Baltimore/Washington (MS)	8.43	0.09 [0.02]	130 [18]	11.27 [2.36]
Boise (W)	0.64	0.11 [0.02]	119 [20]	12.49 [3.07]
Boston (NE)	5.61	0.09 [0.02]	128 [19]	11.42 [3.05]
Buffalo/Rochester (NE)	2.46	0.05 [0.01]	140 [12]	6.91 [1.84]
California (CA)	38.31	0.14 [0.03]	112 [22]	15.79 [2.87]
Charlotte (MS)	2.76	0.07 [0.02]	127 [18]	8.28 [2.36]
Chicago (GL)	9.07	0.08 [0.02]	132 [29]	9.94 [2.68]
Cincinnati/Dayton (GL)	2.96	0.07 [0.02]	120 [23]	7.93 [2.56]
Columbus (GL)	2.04	0.07 [0.02]	115 [17]	8.06 [2.10]
Dallas/Ft. Worth (SC)	6.66	0.16 [0.03]	88 [13]	14.15 [2.56]
Denver (W)	3.93	0.17 [0.04]	117 [17]	20.12 [3.62]
Detroit (GL)	4.78	0.07 [0.02]	118 [20]	7.72 [1.84]
Grand Rapids (GL)	1.7	0.09 [0.03]	130 [27]	11.64 [2.95]
Great Lakes (GL)	46.68	0.06 [0.02]	123 [19]	7.68 [1.93]
Harrisburg/Scranton (NE)	4.48	0.05 [0.01]	124 [14]	5.98 [1.62]
Hartford/Springfield (NE)	3.23	0.09 [0.02]	134 [20]	11.53 [2.58]
Houston (SC)	6.32	0.17 [0.03]	85 [13]	14.10 [2.82]
Indianapolis (GL)	2.26	0.06 [0.02]	127 [20]	7.94 [1.97]
Jacksonville (SE)	1.66	0.08 [0.03]	126 [22]	10.17 [3.12]

[9] Standard deviation measures how much on average an observation differs in absolute value from the mean value across all observations in the scanner data sample. Using the top row of the table to illustrate, mean fresh avocado consumption in Albany was 0.06 avocados per week over the study period, with standard deviation of 0.03. Thus, on average Albany consumers bought 0.06 fresh avocados in a week, but an average deviation from this mean was 0.03 avocados per week. The same idea applies to price. Average price in Albany during the study period was $1.26 per avocado, and the average deviation of a weekly price from this mean was 18 cents.

Table 1 Cont.

Market	Mean	Mean [SD]	Mean [SD]	Mean [SD]
	Population (millions)	***Per capita avocados sold***	***ASP (per avocado)***	***Per capita retail sales value***
Las Vegas (W)	2.06	0.14 [0.03]	104 [19]	14.21 [2.68]
Los Angeles (W)	17.47	0.15 [0.03]	102 [22]	14.76 [2.94]
Louisville (MS)	1.27	0.06 [0.02]	125 [20]	7.03 [2.19]
Miami/Ft. Lauderdale (SE)	5.83	0.08 [0.03]	130 [23]	10.02 [3.20]
Midsouth (MS)	38.47	0.07 [0.02]	123 [15]	8.35 [2.01]
Nashville (MS)	1.86	0.09 [0.03]	112 [16]	9.80 [2.70]
New Orleans/Mobile (SC)	3.04	0.08 [0.02]	109 [17]	8.36 [2.11]
New York (NE)	19.82	0.06 [0.02]	138 [21]	8.76 [2.15]
Northeast (NE)	55.89	0.07 [0.02]	132 [17]	8.74 [2.26]
Northern New England (NE)	3.3	0.11 [0.03]	123 [18]	13.59 [3.94]
Orlando (SE)	3.35	0.08 [0.03]	124 [20]	10.09 [3.31]
Philadelphia (NE)	6.55	0.06 [0.01]	137 [18]	7.98 [1.85]
Phoenix/Tucson (W)	5.04	0.2 [0.05]	75 [18]	14.60 [2.54]
Pittsburgh (NE)	2.51	0.04 [0.01]	137 [20]	4.70 [1.45]
Plains (P)	20.95	0.08 [0.02]	120 [17]	9.10 [2.07]
Portland (P)	3.28	0.15 [0.03]	121 [19]	18.14 [3.85]
Raleigh/Greensboro (MS)	3.49	0.07 [0.02]	123 [16]	8.76 [2.27]
Richmond/Norfolk (MS)	2.89	0.08 [0.02]	113 [14]	8.74 [2.11]
Roanoke (MS)	2.36	0.05 [0.01]	115 [15]	6.23 [1.43]
Sacramento (CA)	2.92	0.14 [0.03]	124 [20]	17.59 [3.60]
San Diego (CA)	3.22	0.15 [0.03]	108 [23]	15.57 [2.90]
San Francisco (CA)	6.39	0.12 [0.03]	133 [28]	15.79 [2.63]
Seattle (W)	3.62	0.13 [0.03]	137 [21]	18.09 [3.78]
South Carolina (SE)	5.27	0.06 [0.02]	119 [16]	6.72 [1.87]
South Central (SC)	38.19	0.14 [0.03]	90 [12]	12.39 [2.27]
Southeast (SE)	42.34	0.07 [0.02]	122 [19]	8.38 [2.39]
Spokane (W)	0.63	0.12 [0.03]	125 [19]	14.31 [3.10]
St. Louis (P)	2.61	0.07 [0.02]	127 [16]	8.26 [1.58]
Syracuse (NE)	1.16	0.05 [0.02]	136 [11]	6.41 [2.16]
Tampa (SE)	3.62	0.09 [0.03]	126 [22]	10.47 [3.31]
West (W)	34.09	0.16 [0.03]	106 [16]	16.74 [3.13]
West Tex/New Mexico (W)	4.04	0.2 [0.04]	89 [12]	17.46 [3.05]
Total	15.24	0.1 [0.05]	120 [23]	10.95 [4.56]

3.1 Estimation Results and Discussion

We first present results at the weekly level for metropolitan areas and localized regions within the U.S. in table 2, with areas presented in alphabetical order. These results give consumers' response to short-term price changes at retail, such as would occur if fresh avocados were featured on a weekly sales special by retailers in the area or if there were a short-run disruption in the supply chain causing a temporary spike in prices. These estimates all have a very high level of statistical precision. This is indicated in terms of the statistical significance of each estimated coefficient. Each is significant at the 99.9% confidence interval, meaning we can say with almost 100% assurance that the true impact of price is not zero. The 95% confidence intervals indicated in the table give us the range of values wherein we can say with 95% confidence the true value of the price elasticity lies.

Table 2. Market-Level Elasticities and Confidence Intervals, Weekly

Market Area	Elasticity Estimate	95% Confidence Interval
Albany	-1.0576***	(-1.1512 , -0.9640)
Atlanta	-1.2373***	(-1.3106 , -1.1640)
Baltimore/Washington	-1.0604***	(-1.1234 , -0.9974)
Boise	-0.7092***	(-0.8215 , -0.5970)
Boston	-1.1861***	(-1.2503 , -1.1219)
Buffalo/Rochester	-1.1547***	(-1.2591 , -1.0503)
Charlotte	-0.9693***	(-1.0308 , -0.9078)
Chicago	-1.0294***	(-1.1004 , -0.9584)
Cincinnati/Dayton	-1.0227***	(-1.1163 , -0.9291)
Columbus	-1.2601***	(-1.3517 , -1.1685)
Dallas/Ft. Worth	-0.7674***	(-0.8335 , -0.7014)
Denver	-1.3895***	(-1.4815 , -1.2975)
Detroit	-1.5118***	(-1.5982 , -1.4255)
Grand Rapids	-1.5465***	(-1.6130 , -1.4800)
Harrisburg/Scranton	-1.0306***	(-1.1086 , -0.9526)
Hartford/Springfield	-1.0689***	(-1.1257 , -1.0122)
Houston	-0.9045***	(-0.9747 , -0.8343)
Indianapolis	-1.1002***	(-1.1763 , -1.0240)
Jacksonville	-1.3799***	(-1.4377 , -1.3222)
Las Vegas	-1.0652***	(-1.1397 , -0.9907)

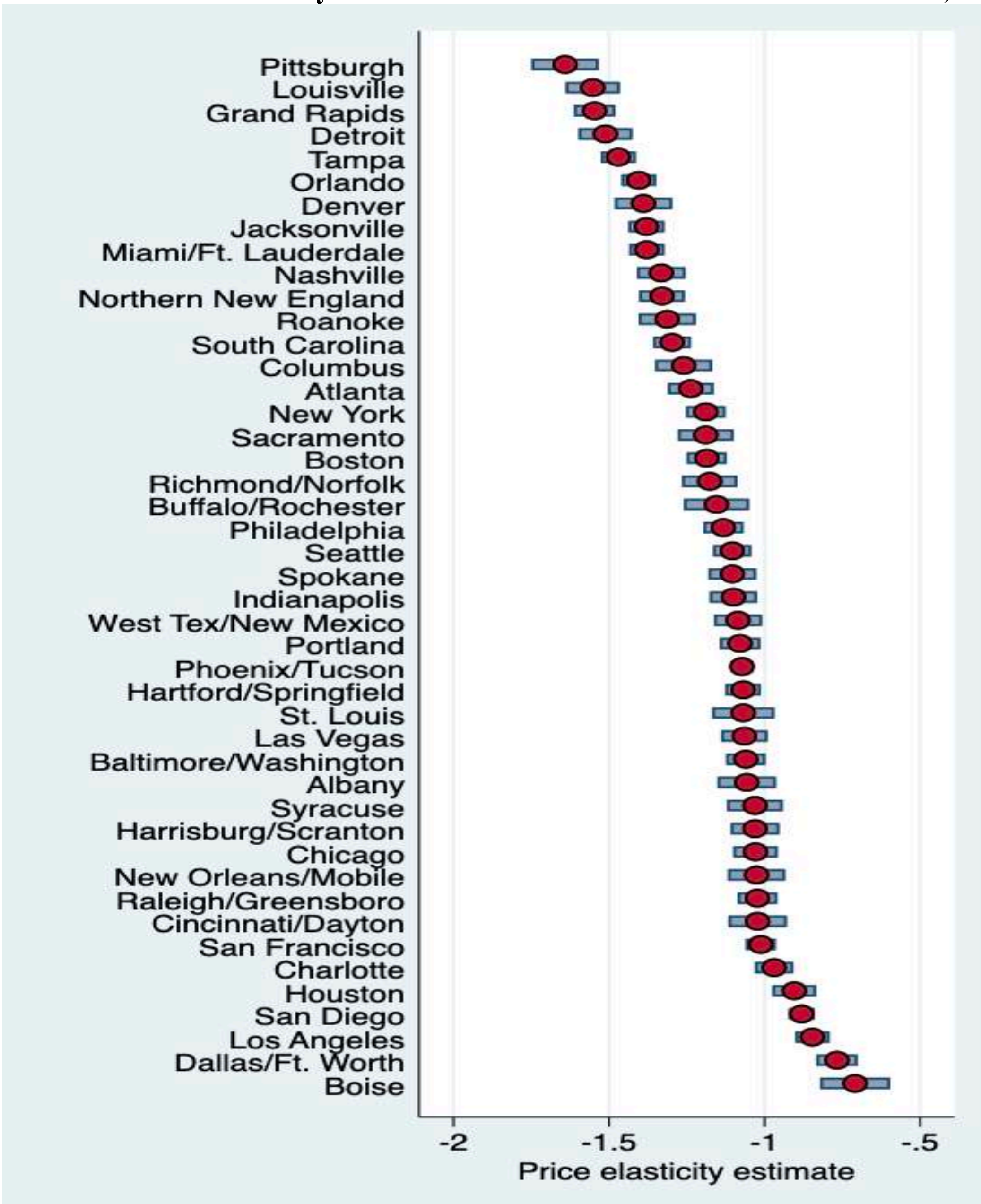
Table 2. Cont.		
Market Area	**Elasticity Estimate**	**95% Confidence Interval**
Los Angeles	-0.8465***	(-0.9016 , -0.7915)
Louisville	-1.5525***	(-1.6394 , -1.4656)
Miami/Ft. Lauderdale	-1.3788***	(-1.4351 , -1.3224)
Nashville	-1.3321***	(-1.4098 , -1.2545)
New Orleans/Mobile	-1.0260***	(-1.1177 , -0.9343)
New York	-1.1892***	(-1.2523 , -1.1262)
Northern New England	-1.3299***	(-1.4029 , -1.2568)
Orlando	-1.4045***	(-1.4599 , -1.3491)
Philadelphia	-1.1325***	(-1.1968 , -1.0683)
Phoenix/Tucson	-1.0727***	(-1.1087 , -1.0368)
Pittsburgh	-1.6415***	(-1.7489 , -1.5341)
Portland	-1.0791***	(-1.1441 , -1.0140)
Raleigh/Greensboro	-1.0232***	(-1.0869 , -0.9594)
Richmond/Norfolk	-1.1765***	(-1.2651 , -1.0880)
Roanoke	-1.3130***	(-1.4045 , -1.2216)
Sacramento	-1.1891***	(-1.2784 , -1.0999)
San Diego	-0.8808***	(-0.9225 , -0.8391)
San Francisco	-1.0124***	(-1.0606 , -0.9643)
Seattle	-1.1041***	(-1.1654 , -1.0428)
South Carolina	-1.2973***	(-1.3578 , -1.2368)
Spokane	-1.1039***	(-1.1802 , -1.0275)
St. Louis	-1.0687***	(-1.1684 , -0.9691)
Syracuse	-1.0311***	(-1.1205 , -0.9417)
Tampa	-1.4703***	(-1.5264 , -1.4142)
West Tex/New Mexico	-1.0856***	(-1.1624 , -1.0088)
Observations	258	

*** $p<0.001$, ** $p<0.005$, * $p<0.01$

Notes: Standard errors allowed to be correlated across markets; month, year, and holiday fixed effects included; model controls for local and national promotion expenditure by week and lag of average sales price.

Figure 2 depicts the same weekly results in graphical form, with metropolitan areas arrayed from top to bottom in order of their estimated price elasticities of demand from the double log model. The blue horizontal bars represent the 95% confidence interval (the range of estimated elasticities that would be obtained in 95 out of 100 samples of the type used in this report). The red markers indicate the point estimates for the price elasticity of demand.

Figure 2. Market Price Elasticity Point Estimates and 95% Confidence Intervals, Weekly



Most of the estimated elasticities are greater than 1.0 in absolute value, meaning weekly demands are generally quite elastic or responsive to price. For example, we estimate that the elasticity of weekly fresh avocado demand in the Denver area is -1.39. Suppose a number of major retailers in the Denver area featured fresh Hass avocados on sale in a given week, so that the average price in the Denver area fell by 20%. Our model predicts that sales in the Denver area would increase for that week by -20% x -1.39 = 27.8%.

Los Angeles is one of the few markets estimated to have a somewhat inelastic demand for fresh Hass avocados. Its weekly demand has an estimated price elasticity of -0.85. Thus, the same hypothetical sale on fresh avocados in the Los Angeles market is predicted to generate a sales increase of -20% x -0.85 = 17.0%.

The estimated price elasticities range from a low of -0.71 in Boise, Idaho to a high of -1.64 in Pittsburgh, so the models predict consumers in Pittsburgh are twice as responsive to price of fresh avocado as are consumers in Boise. Most of the elasticity estimates are quite similar, with 80% falling in the range of -1.5 to -1.0.

Table 3 and figure 3 present the same information as in table 2 and figure 2 except that now we evaluate the response in metropolitan areas of fresh Hass avocado sales to their average price in the metropolitan area over a time interval of one month. In other words, we aggregate the weekly IRI sales and value-of-sales data to the month level and compute average sales price over the month. With monthly data, we measure the impact on consumption of longer-term price changes that could occur, for example, due to fluctuations in shipments to the U.S. market based on harvest conditions in California and the importing countries. We expect to see a reduced response of demand to price changes over this longer time interval. In estimations conducted for the promotion-evaluation study, Ambrozek, Saitone, and Sexton (2018) showed that there was a "rebound effect" to price promotions, wherein one-fourth to one-third of the sales impact from a price change in a given week was offset the following week. For example, consumers who accelerate their fresh avocado purchases in week *t* in response to a favorable price in that week were found to reduce purchases the following week by an average of one-fourth to one-third.

Monthly data will reflect more of a long-term response of consumption to price than the weekly data.

Table 3. Market-Level Elasticities and Confidence Intervals, Monthly

Market	Elasticity Estimate	95% Confidence Interval
Albany	-0.4711***	(-0.5531 , -0.3890)
Atlanta	-0.6188***	(-0.6724 , -0.5651)
Baltimore/Washington	-0.4950***	(-0.5478 , -0.4422)
Boise	-0.6970***	(-0.7923 , -0.6017)
Boston	-0.4898***	(-0.5544 , -0.4252)
Buffalo/Rochester	-0.7737***	(-0.8576 , -0.6899)
Charlotte	-0.5213***	(-0.5639 , -0.4787)
Chicago	-0.7798***	(-0.8168 , -0.7427)
Cincinnati/Dayton	-0.3977***	(-0.4509 , -0.3445)
Columbus	-0.8642***	(-0.9267 , -0.8017)
Dallas/Ft. Worth	-0.5746***	(-0.6212 , -0.5279)
Denver	-0.8922***	(-0.9678 , -0.8166)
Detroit	-1.0199***	(-1.0747 , -0.9651)
Grand Rapids	-1.2220***	(-1.2697 , -1.1743)
Harrisburg/Scranton	-0.6674***	(-0.7264 , -0.6084)
Hartford/Springfield	-0.6002***	(-0.6432 , -0.5572)
Houston	-0.5656***	(-0.6245 , -0.5067)
Indianapolis	-0.7156***	(-0.7584 , -0.6727)
Jacksonville	-1.0107***	(-1.0625 , -0.9588)
Las Vegas	-0.7844***	(-0.8374 , -0.7314)
Los Angeles	-0.6075***	(-0.6585 , -0.5565)
Louisville	-0.9795***	(-1.0324 , -0.9265)
Miami/Ft. Lauderdale	-1.1472***	(-1.1946 , -1.0998)
Nashville	-0.6386***	(-0.6811 , -0.5962)
New Orleans/Mobile	-0.7776***	(-0.8445 , -0.7108)
New York	-0.7509***	(-0.8046 , -0.6971)
Northern New England	-0.6920***	(-0.7508 , -0.6332)
Orlando	-1.1017***	(-1.1573 , -1.0462)
Philadelphia	-0.6943***	(-0.7446 , -0.6439)
Phoenix/Tucson	-0.7798***	(-0.8137 , -0.7459)
Pittsburgh	-1.1053***	(-1.1902 , -1.0204)
Portland	-0.9537***	(-1.0017 , -0.9057)
Raleigh/Greensboro	-0.5007***	(-0.5410 , -0.4605)
Richmond/Norfolk	-0.7468***	(-0.7978 , -0.6957)
Roanoke	-0.8619***	(-0.9099 , -0.8139)
Sacramento	-0.8390***	(-0.8919 , -0.7860)
San Diego	-0.7051***	(-0.7485 , -0.6618)
San Francisco	-0.7997***	(-0.8382 , -0.7613)

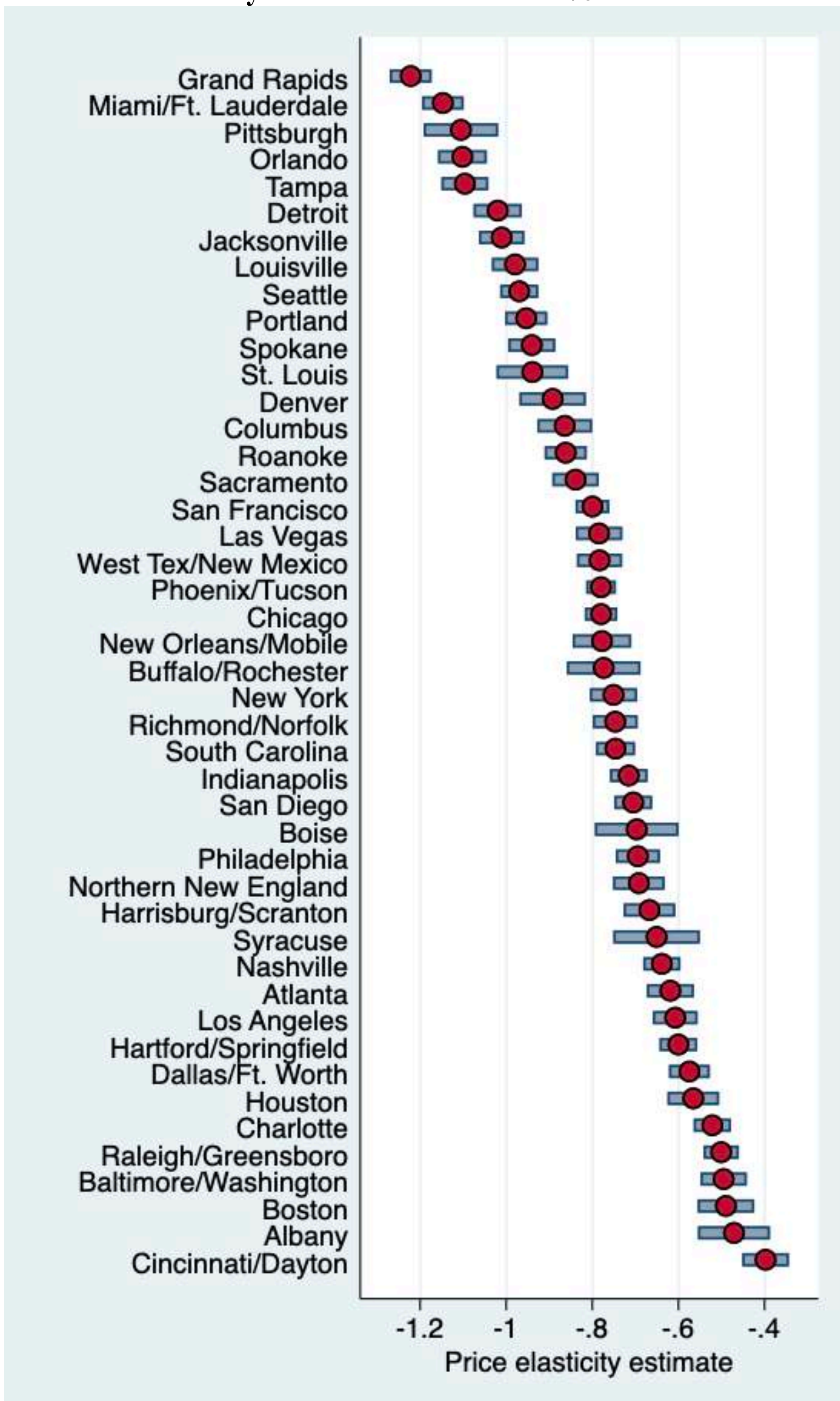
Table 3. Cont.		
Market	**Elasticity Estimate**	**95% Confidence Interval**
Seattle	-0.9699***	(-1.0133 , -0.9264)
South Carolina	-0.7463***	(-0.7908 , -0.7018)
Spokane	-0.9407***	(-0.9943 , -0.8871)
St. Louis	-0.9394***	(-1.0208 , -0.8579)
Syracuse	-0.6508***	(-0.7493 , -0.5523)
Tampa	-1.0961***	(-1.1497 , -1.0426)
West Tex/New Mexico	-0.7834***	(-0.8350 , -0.7317)
Observations	60	

*** $p<0.01$, ** $p<0.05$, * $p<0.1$

Notes: Standard errors allowed to be correlated across markets; year fixed effects included; model controls for local and national promotion expenditure by month.

Table 3 and figure 3 confirm the intuition that response to price over the longer term will be less elastic. Once again impacts of price on fresh avocado sales are measured with high precision as indicated by the high degree of statistical significance of each individual estimate and the relatively tight bands around the estimate created by the 95% confidence intervals. For all markets the sales response to price over a monthly window is less than was observed in the weekly data. Indeed, most of the metropolitan market demands are now price inelastic in that the estimated elasticities are less than 1.0 in absolute value, although several estimates are just greater than 1.0 in absolute value and thus still somewhat elastic. Returning to our examples of Denver and Los Angeles, we see that a 20% price increase on average across Denver retailers over a representative month, e.g., due to reduced harvests from one or more key producing locations, would reduce sales in the Denver market by 20% x -0.89 = -17.8%. In Los Angeles the sales response to the same increase in price is predicted to be 20% x -0.61 = -12.2%.

Figure 3. Market Price Elasticity Point Estimates and 95% Confidence Intervals, Monthly



We should also note that these elasticities can also be used "in reverse." We are estimating the shape of the fresh Hass avocado demand curve (the relationship between consumption and price) in different markets, while accounting for the other factors besides price that impact sales. For shippers, a relevant question to ask is how do incremental sales to a market impact price in that market? For example, in favorable crop years shippers may have more avocados to market in the U.S. than had been anticipated. The elasticity of price with respect to total shipments or sales is simply the inverse of the elasticity of fresh avocado sales to price. For example, consider the monthly model and the estimates for Denver and Los Angeles. Suppose we increase shipments to each of these markets by 10% in a given month. Then our models forecast the following effects on price in each market area:

Denver: 10% x (-1/0.89) = -12.4%
Los Angeles: 10% x (-1/0.61) = -16.4%.

The model predicts that average price in the Denver market would fall by 12.4% and in the LA market price would fall by 16.4%. To the extent shippers can target incremental shipments to specific markets, they should target the markets with the most elastic demands because those markets can absorb the shipments with the least impact on prices in the market.

3.2 Price Elasticities by Region

Next, we turn our attention to the decomposition of the U.S. into eight regions in the IRI data. IRI defines regions in the U.S. as follows: California, Great Lakes, Midsouth, Northeast, Plains, South Central, Southeast, and West. The regional designation of each metropolitan area is indicated in parentheses in table 1. Table 4 and figure 4 present the regional results based on the weekly data. As in the previous figures, in figure 4, the point estimate of the elasticity is indicated by the red dot, while the 95% confidence interval is shown by the blue bar. Once again, the results are highly statistically significant and have tight confidence intervals.

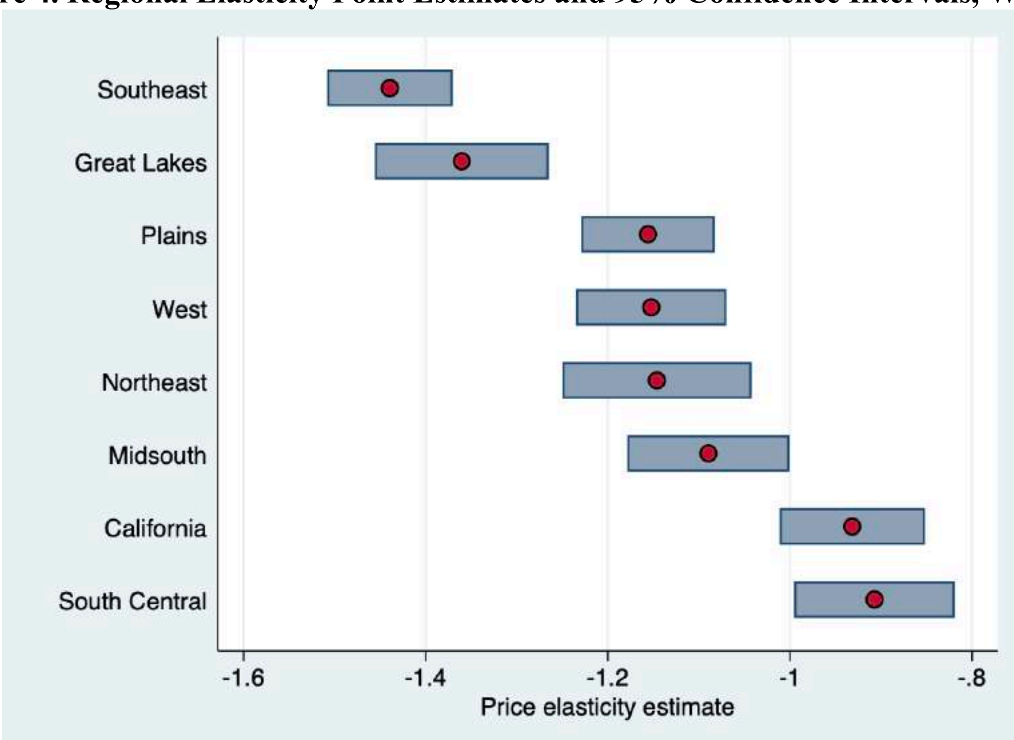
Table 4. Regional Elasticities and Confidence Intervals, Weekly

Region	Elasticity Estimate	95% Confidence Interval
California	-0.9316***	(-1.0111 , -0.8522)
Great Lakes	-1.3605***	(-1.4557 , -1.2653)
Midsouth	-1.0896***	(-1.1783 , -1.0008)
Northeast	-1.1461***	(-1.2496 , -1.0426)
Plains	-1.1559***	(-1.2291 , -1.0827)
South Central	-0.9072***	(-0.9950 , -0.8194)
Southeast	-1.4394***	(-1.5078 , -1.3710)
West	-1.1524***	(-1.2346 , -1.0702)
Observations	258	

*** p<0.001, ** p<0.005, * p<0.01

Notes: Standard errors allowed to be correlated across markets; month, year, and holiday fixed effects included; model controls for local and national promotion expenditure by week and lag of average sales price.

Figure 4. Regional Elasticity Point Estimates and 95% Confidence Intervals, Weekly



As expected, the elasticities at the regional level are broadly comparable to those estimated for metropolitan areas. Retail demand is somewhat price elastic in six of the eight regions and slightly inelastic in California and the South-Central region. The most price elastic region is the Southeast, with an estimate of -1.44, followed by the Great Lakes, with an estimate of -1.36.

The monthly models by region are shown in table 5 and figure 5. As was true for the metropolitan areas, regional demand is less responsive to price changes over a longer interval. All eight of the regions show inelastic demands when viewed over monthly horizons, with California and South Central once again being the regions that are most unresponsive to price. Notable is that both California and the South-Central region are areas of high per capita consumption of fresh avocados based on table 1. Over the study period weekly per capita consumption was 0.14 in both California and the South-Central region, compared to a national weekly average of 0.1.

Table 5. Regional Price Elasticity Estimates and Confidence Intervals

Region	Elasticity Estimate	95% Confidence Interval
California	-0.7987***	(-0.9123 , -0.6850)
Great Lakes	-0.9568***	(-1.0575 , -0.8561)
Midsouth	-0.7094***	(-0.8359 , -0.5830)
Northeast	-0.8789***	(-1.0500 , -0.7078)
Plains	-0.8649***	(-0.9887 , -0.7411)
South Central	-0.7356***	(-0.8473 , -0.6239)
Southeast	-0.9407***	(-1.0631 , -0.8184)
West	-0.9581***	(-1.0619 , -0.8544)
Observations	60	

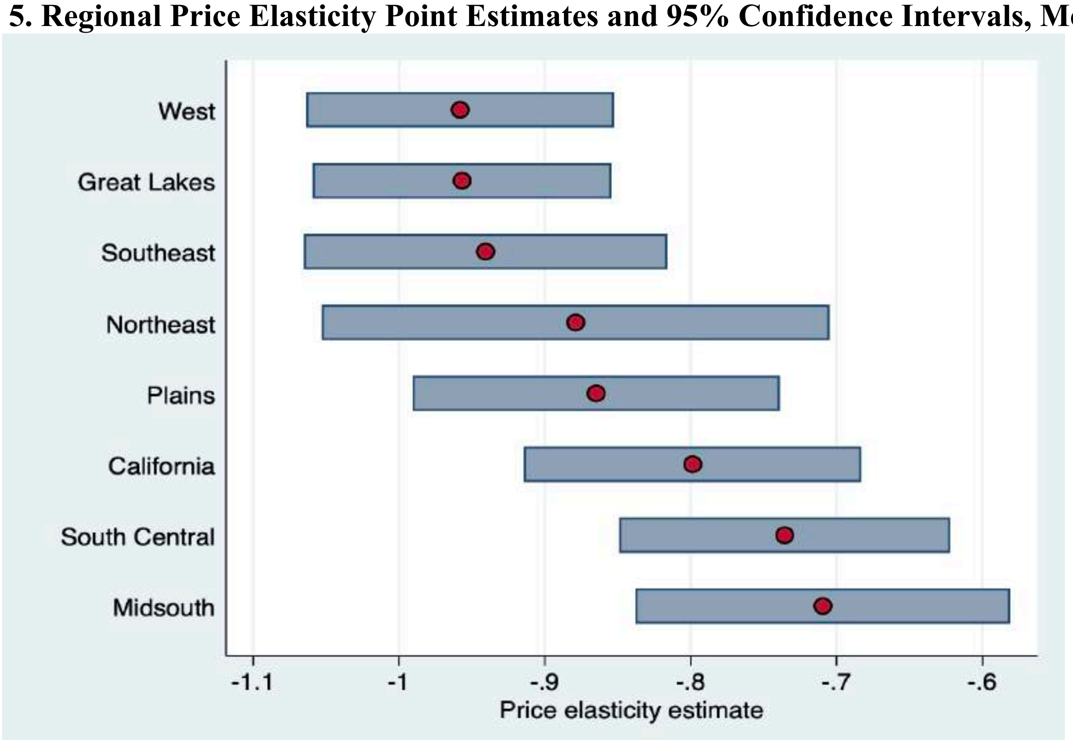
*** p<0.01, ** p<0.05, * p<0.1

Notes: Standard errors allowed to be correlated across markets; year fixed effects included; model controls for local and national promotion expenditure by month.

It is intuitive that regions of high per capita consumption are the most price inelastic because people have made fresh avocados part of their staple diets and are unlikely to alter consumption much in response to price changes. It is notable that the Western region (excluding California) is the exception to this pattern. It is a high per capita consumption region that has a quite price elastic demand.

To test the intuition that demand will tend to be less elastic in areas with high capita consumption, we estimated the correlation coefficient between the estimated price elasticity of demand and per capita consumption for the metropolitan-area and local regional markets. We find a negative correlation of -0.293 between the estimated elasticity in absolute value and consumption.[10] Thus, there is a relationship in the data that is consistent with the intuition; areas with greater per capita consumption tend to have less elastic demands. We also examined the correlation between price elasticity and average sales price in these same markets, finding a positive correlation of 0.198. This result suggests that where prices are higher on average, individuals have a larger demand response to a given percent change in price. While these correlations are suggestive, they are not large in magnitude, implying that the underlying relationships are relatively weak.

Figure 5. Regional Price Elasticity Point Estimates and 95% Confidence Intervals, Monthly



[10] These correlations are done with absolute values of the estimated elasticity, so that increasing the elasticity here refers to the magnitude.

3.3 Retail Price Elasticities at the National Level

We present results for the national model in table 6. Here retail sales are aggregated to the national level and aggregated over monthly time intervals to correspond to the availability of monthly data on importer prices. We include estimates of the model in both its linear and double log forms. As noted, elasticities for the linear model are not constant, and vary at different points along the demand curve. Thus, the analyst must choose price and quantity values at which to evaluate the elasticity in the linear model. We chose the means of price and per capita sales over the five-year period, 2013 – 2017, included in the estimation and the means of monthly price and per capita sales for the most recent year, 2017.

Results at the retail level are very consistent with what has already been presented for the regional market aggregates. National demand at retail for fresh Hass avocados is slightly price inelastic; the estimate from the double log model (column 4) is -0.892. The estimate from the linear model (column 3) is very similar, -0.880 or -0.888 depending on whether we evaluate the elasticity at the overall data mean or at the 2017 data mean. Both values are estimated with a high degree of statistical precision. If retail prices rise 10% on average across the nation in a given month, we expect about a 9% decline in retail sales based on either model.

3.4 Shipper Price Elasticities at the National Level

Columns (1) and (2) in table 6 represent estimates of fresh Hass avocado demand at the grower-shipper level. Quantities at this stage of the market chain are essentially the same as at retail, except for a small percentage of fruit that is lost due to damage or spoilage in the shipping process. Prices, however, are considerably different. Importer average prices are available on a per pound basis, whereas the IRI retail prices are per avocado. We converted the importer prices to a per-avocado basis using the assumption that an average Hass avocado weighs 150 grams or

0.331 lbs.[11] The estimated price elasticity of demand at the shipper level based upon the monthly data is -0.189 for the double log model and -0.212 or -0.244 for the linear model, depending on whether the elasticity is evaluated at the overall data means or the 2017 data means. Both estimates are statistically significant.

Table 6. National Model Estimation Results

VARIABLES	(1) Linear Model	(2) Double-Log Model	(3) Linear Model	(4) Double-Log Model
	Shipper Demand		*Retail Demand*	
Price				
Deflated Importer Unit Value ($/Lb.)	-62.069**			
	(27.327)			
Natural Log of Importer Unit Value ($/Lb.)		-0.189*		
		(0.100)		
Average Sale Price (Cents/unit)			-100.717***	
			-30.452	
Log of Average Sale Price				-0.892***
				(0.261)
Promotions				
HAB Association Promotions ($ 000,000)	3.133**		2.650**	
	(1.274)		(1.282)	
Natural Log of HAB Assoc. Promotions ($ 000,000)		0.058**		0.049**
		(0.023)		(0.023)
Constant	115.891***	4.429***	194.317***	4.613***
	(10.392)	(0.126)	(30.607)	(0.051)
Month Fixed Effects	YES	YES	YES	YES
Year Fixed Effects	YES	YES	YES	YES
Observations	60	60	60	60
R-squared	0.675	0.693	0.720	0.741
Elasticity evaluated at mean	-0.212		-0.880	
Elasticity at 2017 mean values	-0.244		-0.888	

Robust standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1

Thus, we estimate that the demand for fresh Hass avocados at the shipper level is highly price inelastic. A 10% decrease in shipper price will only stimulate about 2% additional sales at retail. Using the elasticity in "reverse" as we discussed previously, we can predict based on this

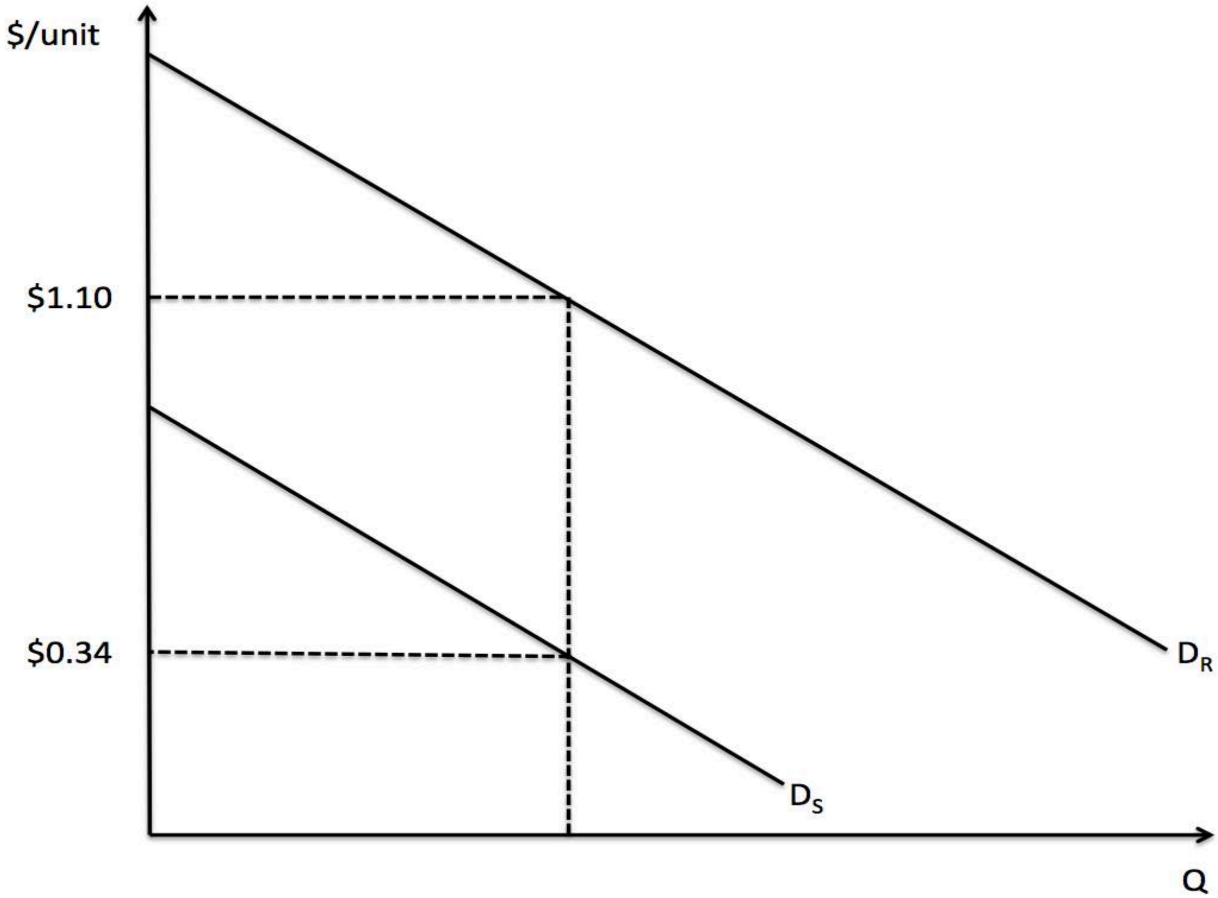
[11] This conversion number is obtained from https://avocadosfrommexico.com/avocado-nutrition/.

model that a 2% increase in shipments within a given month would decrease shipper price by roughly 2% x (-1/0.2) = -10%, where we use -0.2 as a rough average of the elasticities from the double log and linear models.

This finding that demand for fresh Hass avocados is highly inelastic at the shipper level is consistent with what agricultural economists have found for a great many agricultural commodities—derived demand, i.e., the demand facing growers or shippers, is highly inelastic. Inelastic demand is a key reason why farm prices are highly volatile for so many commodities including avocados—even small shifts in supply generate much larger and opposite changes in price.

Figure 6 helps in understanding why fresh avocado demand at the shipper level is so price inelastic even though the demand at the retail level is only slightly price inelastic. Using the linear representation of demand for convenience, we plot total demand at retail for fresh Hass avocados so that the demand exactly fits the observed mean price (per avocado) and retail sales for 2013 – 2017 and label this demand as D_R. Then below it in the same graph we depict the shipper-level demand that is implied by the retail demand. We draw the shipper-level demand so that it exactly fits the same volume of shipments as were sold at retail (essentially assuming away any small volume loss due to spoilage or other damage) and mean shipper price (per avocado) for 2013 – 2017. The vertical gap between the two demands represents markup by retailers to reflect their costs and profit margins. Based on the 2013 – 2017 averages this gap is \$1.10 – \$0.342 = \$0.758.

Figure 6. The Relationship Between Demands at the Retail and Shipper Levels



Let us now consider a small increase in price at both the shipper and retailer levels of the market of $0.10 per avocado. The change in quantity demanded of fresh avocados is the same at both shipper and retailer levels, but $0.10 at the shipper level is a (0.10/0.342) x 100 = 29% increase, while at the retail level, it is a (0.10/1.10) x 100 = 9% increase. Based upon our estimates, this 9% increase in price at retail would reduce retail sales by 9% x 0.892 = -8.03%, using the elasticity estimate from the double log model. Because retailer and shipper volumes are the same, this same percentage sales reduction applies at the shipper level, in which case if we take -8.03%/29%, we get an implied price elasticity of demand at the shipper level of -0.275, a number strikingly close to what we estimated statistically for the shipper-level price elasticity.

Readers should bear in mind that these estimates represent the relationship between price and volume holding all other factors that impact demand constant—in economics parlance it represents movement along a static demand curve. Of course, the demand in the U.S. for fresh avocados has not been static over time; it has been growing for a variety of reasons including the industry's promotion activities, as discussed in our companion report. Thus, to the extent casual observation suggests that shipments to the U.S. have been increasing, but price has not fallen, it is because demand has been growing. These price elasticity estimates are a stark reminder to the industry of the probable price impacts from expanding shipments if demand growth does not continue.

4 Applications

We have discussed several applications of these results in presenting the estimated elasticities, so this section will be brief. Estimates of weekly price elasticities at metropolitan areas can give a sense of the effectiveness of price promotions as a tool to expand sales. We lacked data at the level of individual retail stores. The demand for fresh avocados at a given retailer will certainly be much more elastic than the demand across the entire metropolitan area because a single retailer that features fresh avocados on sale (when its rivals do not) will attract some consumers who ordinarily shop at other retailers. Such price promotions are not very effective from growers' or shippers' perspectives, however, if they merely transfer sales from other retailers to the retailer who is featuring avocados on sale. The elasticity we estimate for an entire metropolitan area is probably a good estimate of the net gain in sales from a subset of retailers in the area featuring avocados on sale in a given week. Here we find that most, but not all, metropolitan areas have mildly elastic demands for fresh avocados—a given percent decrease in price will induce a somewhat larger (in percent terms) positive increase in sales. The more elastic is an area's demand, the more responsive are sales to price, so, to the extent shippers can influence retailers' price promotions, they are wise to target price promotions in the areas with more elastic demands. The monthly models produced less elastic demands in all cases. These demands account for the "rebound effect" of high sales in one week due to fresh avocados being on price promotion being offset by a factor of one-fourth to one-third by an opposite impact on sales in the following week when the product is off promotion.

Using the elasticities in reverse, then areas with more elastic demands can absorb more sales with less impact on price. Thus, shippers with extra avocados to move due to a large harvest are better off targeting them to the regions and markets with more elastic demands to the extent such targeting is possible.

Whereas markets with relatively inelastic demands are not good candidates for price promotions, they are good candidates for advertisements and other non-price promotions. The reason is that a demand shift achieved through promotions translates into a greater impact on price and a lesser impact on sales in the inelastic-demand markets. This will increase the incremental grower and shipper profit from the promotions. An old, but famous and important result in marketing is known as the Dorfman-Steiner condition (Dorfman and Steiner 1954), which says that the optimal advertising-to-sales ratio for a monopolist is equal to the ratio of the elasticity of demand with respect to advertising expenditure to the absolute value of the price elasticity of demand. Mathematically, if we let A denote advertising expenditure, and S denote sales volume, each measured, for example, in dollars, and we let ε_A and η respectively denote the elasticity of demand with respect to advertising expenditure and with respect to price, the Dorfman-Steiner condition is:

$$\frac{A}{S} = \left|\frac{\varepsilon_A}{\eta}\right|.$$

The more effective promotions are, as measured by ε_A and the less elastic is demand, as measured by $|\eta|$, the greater is the optimal advertising intensity. Importantly, UC Davis agricultural economists Julian Alston, Jim Chalfant, and Hoy Carman (1994) showed that the Dorfman-Steiner result also characterizes optimal advertising intensity for a commodity board. To apply the Dorfman-Steiner result, we continue with our examples of Denver and Los Angeles. Using the weekly model estimates of price elasticities obtained in this study and the weekly estimate of the promotion elasticities, $\varepsilon_A = 0.0162$, from our companion report (Table 10, column (1)), we have:[12]

Denver: A/S = 0.0162/1.3895 = 0.0117

Los Angeles: A/S = 0.0162/0.8465 = 0.0191.

We can compare these estimates of the optimal A/S ratio for each metropolitan area to what we estimate the actual ratios were over the five-year period, 2013 – 17, studied in our companion report on promotion evaluation. The actual ratios are 0.0151 for Los Angeles and 0.0084 for Denver. In each case, the actual ratio is less than what would have been optimal based on Dorfman-Steiner. The optimal A/S ratio is higher in Los Angeles than in Denver because the former has a more price inelastic demand for fresh avocados.

In concluding this discussion, we should note a couple of caveats. First, promotion expenditures in these markets declined in the later years of our study, indicating that the industry was moving further from the optimum in the most recent years. Second, as noted in the companion study, we regard $\varepsilon_A = 0.0162$ as a conservative estimate. For example, our estimate of the national promotion elasticity based on monthly data was $\varepsilon_A = 0.058$, nearly four times

[12] We did not attempt to estimate unique promotion elasticities for each metropolitan area in our companion report on promotion evaluation.

greater and would imply a commensurately greater optimal A/S ratio if we applied that number in the Denver and Los Angeles examples.

Finally, we can use these estimated elasticities to generate rough forecasts of price impacts from year-to-year or season-to-season changes in shipment volumes, assuming demand is otherwise constant. For example, suppose the average shipper price in a given month in the prior year was P_1 dollars per ton. Based on industry forecasts, shipments are expected to be 5% higher in the current year, then our analysis predicts that the shipper price will fall by about 25%, given an estimated price elasticity of about -0.2, so a forecast of the monthly shipper price would be $P_2 = 0.75P_1$. Again, this forecast assumes no shift in demand. In reality, the industry has been effective at increasing demand over time, so the actual price decrease would be less than this simple tool predicts, if demand grew from year to year. This predicted price effect with no growth in demand could be considered a worst-case outcome on price due to expanded shipments.

5 Conclusion

We have shown that the estimated price elasticities of demand for Hass avocados vary not only across markets and regions in the U.S., but that the level of aggregation in space and time, and the market level at which the elasticity is evaluated are important for the size of the effect. These differences can be explained by economic theory, and are important to understand for growers, shippers, and marketers of avocados. Targeting price promotions and excess shipments to areas with more elastic demands, and advertisements and non-price promotions to areas with less elastic demands are strategies for maximizing the effectiveness of promotions.

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