UCR SPP Working Paper Series

July 2021 – WP#21-01

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Summary:

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Acknowledgements: Funding for this research was provided by the California Citrus Research Board Project #5400-158 and the Giannini Foundation of Agricultural Economics.

Estimation of Supply Elasticities for Non-Exchange Traded Commodities

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The standard method for estimating crop supply elasticities is to regress acreage or quantity produced on futures prices which are assumed to represent grower expectations about post-harvest price levels. This method cannot be applied to most crops because relatively few crops are traded on futures exchanges. We present an alternative method that substitutes demand shifts for expected price in regressions. Supply elasticities are then inferred from regression results by making the assumption of rational expectations. A potential difficulty in applying this method is that knowledge of the crop demand elasticity is needed to identify demand shifts. We present a non-regression-based method for joint calibration of demand elasticities and demand shifts using crop and market information knowledge. We apply our method to four tree crops which are not traded on futures exchanges and two annual crops which are. The two annual crops are included to provide verification that our method generates elasticities that agree with high-quality literature estimates. Using data from 1995 to 2019, we estimate most likely acreage supply elasticities for almonds, mandarins, pistachios, and walnuts of 0.47, 0.79, 1.37, and 0.24, respectively. Using the same method, we estimate supply post-ethanol supply elasticities for corn and soybeans of 0.11 and 0.14, respectively

Key words: Crop supply elasticity, Crop demand elasticity, Demand shifts

JEL codes: Q11, Q13

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Introduction

Estimation of agricultural crop supply elasticities usually proceeds by regressing quantity on price. Time differences between supply decisions and subsequent price determination leads to the use of expected or planning prices in regressions. For commodities with futures markets, Feder, et al. (1980) demonstrated that a firm's production decisions are independent of risk attitudes and subjective beliefs about the distribution of future prices at supply-decision time, thus justifying the use of futures prices as a measure of the expected price (Hendricks, et al., 2015, Kim and Moschini, 2018, Miao, et al., 2016, Roberts and Schlenker, 2013). An econometric benefit of using futures prices in supply regressions is that they are usually treated as predetermined with respect to realized production, thereby avoiding simultaneity bias. When a commodity is not traded on a futures exchange, analysts must judge what information growers use to form expectations about future profitability to form a measure of the expected price. The most common measure used is to assume that growers form their price expectations based on lagged market prices or revenues (Carman and Green, 1993, Kinney, et al., 1987, Russo, et al., 2008).

The problem with using lagged prices to form expectations about future profitability is that they are not likely informationally efficient because lagged prices, by definition, cannot reflect changes in market conditions after the price is measured. Furthermore, significant variations in past market prices caused by unusually poor growing conditions or bumper crops can lead to large changes in measured price expectations even though growers likely view such large swings in prices as being unrepresentative of the future price levels. The justification for using lagged prices is that they can reflect the effects of systemic demand growth or decline, which will ultimately impact future profitability and hence, production decisions.

An alternative to using lagged prices to estimate supply response for commodities without futures is to estimate how supply responds to changes in demand. Bekkerman, et al. (2018) modified an unpublished method that uses observed price-quantity pairs over time to identify demand shifts (Purcell, 1998). The method is straightforward to implement, but it requires knowledge of the slope for a linear demand curve or the own-price elasticity of demand for a constant-elasticity demand curve. Given the slope of a linear demand curve, demand is assumed to have shifted from one year to the next unless both years' points fall on the same line. If the year two quantity is greater than the quantity that would have been consumed using the year-one demand curve, then demand has increased. If the observed quantity is less than would have been consumed, then demand has decreased. The amount of the demand shift is the horizontal difference (using the standard inverse demand curve) between the quantity that we would expect to observe using the year-one demand curve and what we actually observe.

A regression of quantity on the demand shift does not directly lead to supply elasticity estimates because supply elasticities are defined as the response to price changes rather than demand changes. Therefore, an additional step that translates changes in demand to changes in expected price is required. One method to implement this step is to assume that growers have rational expectations and base their price expectations on how much supply will respond—and hence prices—to the changes in demand.

This paper aims to present a new method of estimating supply elasticities for crops without futures prices. Our method relies on regressions of acreage on estimated demand shifts and the assumption of rational expectations. We implement the method for four important tree crops that are not traded using futures prices: almonds, mandarins, pistachios, and walnuts. We also implement the method for corn and soybeans to facilitate a comparison of elasticities estimated using this new method with published estimates based on regressions of quantity on futures prices. An additional contribution of this paper is that we show how the construction of the index of demand shifts over time that we use in our supply response analysis can be used to estimate demand elasticities, which is useful when reliable estimates cannot be found in the literature.

Theoretical Framework

1.1. Demand Shifts

Estimation of demand shifts begins with a time series of observed price-quantity pairs, (p_t, q_t), t = 1,…, T. Let $p_t = f(q_t; Z_t)$ be the inverse demand function for year t where Z_t represents demand shifters such as income and prices of related goods. This specification implies that if demand shifters are constant over time, so is the demand curve's position. Thus, we assume that the functional form and perhaps some parameters of the demand function are time-invariant. Which prices and quantities to use to estimate demand shifts depends on the situation. To study changes in consumer demand requires retail data. To study the demand for farm products requires prices received by farmers and farm-level quantities. Disappearance (i.e., domestic consumption plus net exports) rather than production data should be used because any change in storage drives a wedge between production and consumption.[2] The time step is dictated by data availability and the purpose of the study. If, as is the case in this paper, interest is on estimating annual supply decisions, then annual disappearance data is most relevant. A maintained assumption in this paper is that reported use and price represent a point on a year's demand curve for consumption. We make no assumption about how a year's price is determined.

[2] We treat any exports as being consumed in the importing country.

If no change in demand occurs from year t to t+1, then both (p_t, q_t) and (p_{t+1}, q_{t+1}) lie on the same demand curve, in which case:

(1) $q_{t+1} = f^{-1}(p_{t+1}; Z_t)$

Equation (1) simply means that observed quantity in t+1 equals the quantity that we would expect given observed p_{t+1} and the year t demand curve. No change in demand will occur only if $Z_t = Z_{t+1}$. If demand has shifted, then the change in demand is given by

(2) $\Delta D_{t+1} = q_{t+1} - f^{-1}(p_{t+1}; Z_t)$

Based on equation (2), the demand curve shift in t+1 equals the actual t+1 quantity minus what quantity would have been under the year t demand curve. An index of demand, DI_t, can be easily constructed by setting $DI_1 = 100$ and DI_{t+1} as following:

(3) $DI_{t+1} = DI_{t+1}[1 + \Delta D_{t+1}/f^{-1}(p_{t+1}; Z_t)]$

Implementation of this method requires making a choice about functional form and parameters. Bekkerman, et al. (2018) chose a linear function and solved for the slope using an assumed demand elasticity at the initial price and quantity. Holding the slope constant for each year's observations implies time-varying demand elasticities. An alternative is to choose a constant elasticity demand curve. Regardless of the choice, the resulting time series of estimated demand curve shifts is conditional on the demand elasticity used.

1.2. Demand Elasticity

The generally accepted practice among economists is to estimate the responsiveness of quantity sold to price changes by establishing a relationship between historical market prices and quantities sold. But this exercise will fail without accounting for changes in market conditions that either increase or decrease the ability to sell the product without changing price. For example, California exports fresh navel oranges and competes with Spain, among other countries in export markets. A short crop in Spain increases the ability of California growers to sell their crops. This represents an increase in demand, albeit a temporary one. If California has a bumper crop in the same year, then we could well see market price fall due to the bumper crop, despite an increase in demand. Figure 1 shows how ignoring the size of the Spanish crop gives rise to an incorrect estimate of responsiveness.

In Figure 1, the slope of the line labeled "Original Demand" shows how market price responds to changes in the quantity of oranges that enters the market. This line is the demand curve for navel oranges facing California growers in year 1. The slope of this demand curve is not known, so it is what analysts want to estimate. Data typically used to estimate this slope are annual pairs of prices and quantities. In Figure 1, two pairs are observed. The year one pair is generated in the year before the short crop in Spain and the bumper crop in California. The quantity that California growers produce and want to sell in year 1 is Q_1. The resulting market price is P_1. The second pair is generated in year 2. The increased California production is represented by Q_2. This generates a year 2 price of P_2. If one naively calculates the slope of the line connecting these two pairs, then one would underestimate the responsiveness of price to quantity. That is, the slope of the line labeled "Incorrect demand curve" connecting the year one and year 2 two points is much flatter than the actual slope of the demand curve. Therefore, one cannot calculate the correct slope of the demand curve facing California navel orange growers without accounting for the movement of the demand curve in year 2. The magnitude of this movement is calculated by determining how much could have been sold on the original demand curve at the observed market price P_2. This quantity is Q'_2. The increase in demand caused by the short crop in Spain is $Q_2 – Q'_2$. Note that if demand had not shifted in year two, then the price that California navel growers would have received in year two would have been dramatically lower than what it actually was at P*, which we can only calculate if we know the actual responsiveness of the demand curve.

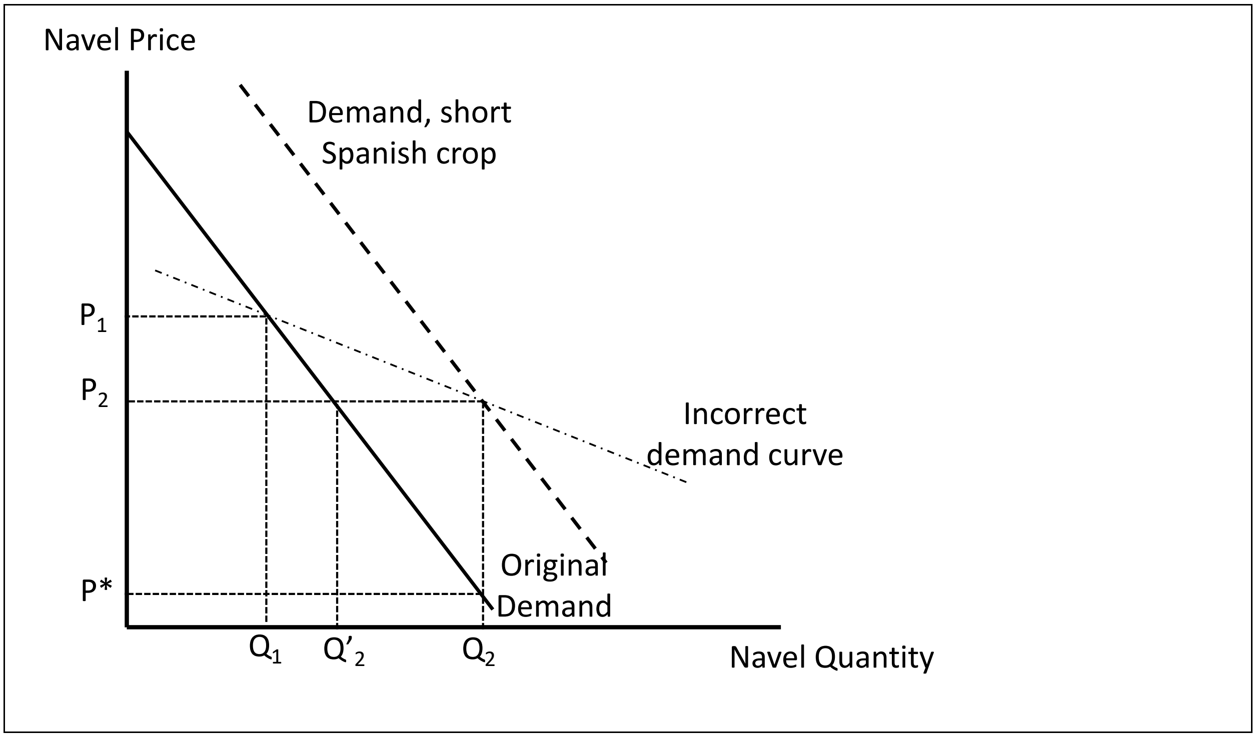

Figure 1. Estimating Responsiveness and Shifts in Demand

Figure 1 illustrates why it is not straightforward to estimate how much demand for tree crops has grown over time. One could erroneously conclude from observed prices and quantities that demand has not grown at all: a lower price facilitated the increased quantity sold. However, if the analyst knew that the short Spanish crop resulted in a demand increase in year two equal to $Q_2 – Q'_2$, then it would be straightforward to calculate the slope of the demand curve by subtracting the demand shift from Q_2 and then calculating the resulting slope. Conversely, if the analyst knew the true slope of the demand curve, then the actual shift in demand could be calculated. This illustrates the problem facing economists: We cannot calculate responsiveness without detailed information about demand shifts, but we cannot calculate demand shifts without detailed information about responsiveness.

The method that we chose to use to estimate demand shifts is to take advantage of the fact that there is a corresponding level of demand shift for any given level of price responsiveness. For example, if we have 40 years of prices and quantities, each candidate's level of responsiveness gives us 39 estimates of demand shift. We then choose the level of responsiveness that generates demand shifts that are most consistent with whatever market information about the crop is available. For example, suppose we know which years Spain has a short crop. In that case, we find the level of price responsiveness of navel oranges that generates demand increases that match up well with information about the likely impact that a short crop in Spain has on the demand for California navels. When possible, we include in our initial candidate price responsiveness published estimates from the literature.

One advantage of calibrating demand elasticity to market information about demand shifts is that the analyst is transparent regarding the use of information. Regression-based estimates require selecting one or more proxies for demand shifts that the analyst believes affect demand throughout the data estimation period. Whether the proxies actually isolate demand shifts from movement along a demand curve consistently throughout the data period is difficult to determine. The analyst must trust that the proxies do a good enough job on average to reveal the underlying demand elasticity.

1.3. Supply Elasticities

By definition, crop supply equals the product of harvested area and yield. Thus, supply elasticity equals the own-price elasticity of area plus the own-price elasticity of yield. Estimation of yield elasticity is difficult because yield is a function of volatile weather, endogenous adoption of exogenously determined technology, as well as input choices. The analyst observes harvested yield but rarely observes choices that determine yield. Hence, it is difficult to separate how input choices are impacted by prices from exogenous yield factors. In contrast, acreage choices are observable, which perhaps explains why acreage elasticities are more commonly estimated than yield elasticities, notable recent exceptions notwithstanding. Here we develop a method to estimate acreage elasticities. As explained below, to the extent that yields are endogenous, our estimates underestimate total supply elasticity as one would expect.

The first step is to establish a relationship between demand shifts and acreage changes by regressing observed acreage on estimated demand shifts. Support for a positive relationship is that increases in demand increase output price if supply is less-than-perfectly elastic, thereby increasing profits and incentivizing area expansion if the demand shift is permanent. The time lag between demand shifts and acreage changes needs careful consideration. Tree crops take multiple years before they bear production. Bearing acreage is the most typical way that acreage is reported, so a change in bearing acreage occurs in response to decisions made three to six years previously, depending on the crop. Annual crop data is most often reported by the marketing year. So, for example, a U.S. corn crop planted in April of year *t* cannot respond to a demand increase calculated from data generated in marketing year *t* because the marketing year begins in September of year *t* in most producing regions. An April-planted crop is only 2/3rds of the way through the *t*-1 marketing year, suggesting that a two-year lag between demand shifts and acreage changes may be most appropriate. We discuss the appropriate lags for the crops included in this paper in the results section. For now, we simply hypothesize that there exists a positive relationship between acreage and relevant demand shifts.

Our method for estimating supply elasticities is most easily explained using Figure 2. In response to a demand increase of $q_2 - q_0$, the equilibrium quantity increases to q_1, and the price increases to p_1. Given the lags between the demand shift and the resulting changes in acreage decisions, we cannot observe p_1 until the increased supply enters the market. Before then the market price will be greater than p_1. The price increase is likely the first information that growers perceive that a market has changed. In a world of rational expectations, growers realize that the immediate price increase will not be sustained because of a subsequent increase in quantity supplied. If growers have the model underlying Figure 1 in their collective minds, then their supply decisions will result in an aggregate increase in production to q_1. If this increase is due to increased acreage, then what the estimated relationship between acreage and demand shifts will reveal is an acreage response to the $q_2 - q_0$ demand shift equal to $q_1 - q_0$. Define the elasticity of acreage with respect to demand shifts as: $\gamma = \frac{\%\Delta A}{\%\Delta D}$. With respect to Figure 1 γ can be defined as follows:

(4) $\gamma = \frac{(q_1 - q_0)/q_0}{(q_2 - q_0)/q_0} = \frac{(q_1 - q_0)}{(q_2 - q_0)}$

We know that total industry acreage should respond less than proportionately to a "*ceteris paribus*" demand shift unless the supply is perfectly elastic, which makes $\gamma \leq 1$.[3]

[3] If our region of interest supplies only a portion of the market then the change in acreage for this region may be greater than one or even negative if acreage in the crop is falling in the region. Here we limit consideration to an entire market.

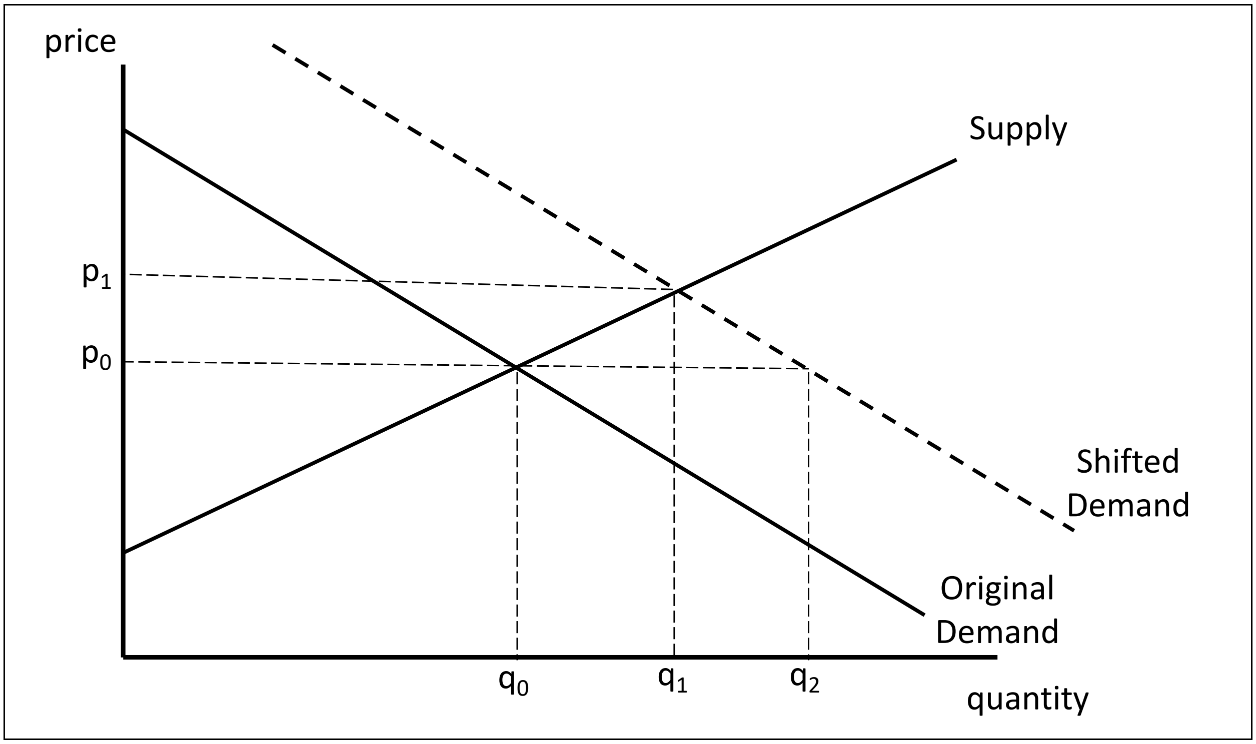

Figure 2. Estimation of Response to Demand Shift

But the acreage response to the demand shift is not a supply elasticity. What is needed is an estimate of the equilibrium percentage price increase that growers expect after the acreage increase. This price increase can be found from the definition of the demand elasticity:

(5) $\eta_D = \frac{\%\Delta q}{\%\Delta p}$ which implies

(6) $\%\Delta p = \frac{\%\Delta q}{\eta_D}$

We want to know how much movement will occur up the demand curve relative to the situation where there is no equilibrium price increase because supply is perfectly elastic. We know that if $\gamma = 1$, then there will be no price increase because supply is perfectly elastic. Thus, we know from Figure 1 that $\%\Delta q = \gamma - 1$.[4] This is the percentage movement up the shifted

[4] A reminder that we assume here that yields are exogenous to changes in output price.

demand curve caused by a less-than-perfectly elastic market supply. Given the demand elasticity η_D we can solve for the price increase:

(7) $\%\Delta P = (\gamma - 1)/\eta_D$

We then know that the supply elasticity is:

(8) $\eta_S = \frac{\eta_D \gamma}{\gamma - 1}$

As γ approaches 1, then supply elasticity becomes perfectly elastic. As γ approaches 0, then the supply elasticity goes to 0. A more elastic demand causes the supply elasticity to increase because a given acreage shift is motivated by less of a price increase. Table 1 shows how estimates of γ and η_D define η_S

Table 1. Calculation of Supply Elasticity from Acreage Response and Demand Elasticity

Acreage Elasticity wrt Demand Shift	Demand Elasticity	Rational Expectations Supply Elasticity
0.3	-0.1	0.04
0.3	-0.3	0.13
0.3	-0.6	0.26
0.3	-0.8	0.34
0.3	-1	0.43
0.5	-0.1	0.10
0.5	-0.3	0.30
0.5	-0.6	0.60
0.5	-0.8	0.80
0.5	-1	1.00
0.7	-0.1	0.23
0.7	-0.3	0.70
0.7	-0.6	1.40
0.7	-0.8	1.87
0.7	-1	2.33
0.9	-0.1	0.90
0.9	-0.3	2.70
0.9	-0.6	5.40
0.9	-0.8	7.20
0.9	-1	9.00

In the next section, we implement the method to estimate supply elasticities of corn and soybeans and tree crops, including almonds, mandarins, pistachios, and walnuts for the United States. Intermediate steps provide estimates of demand shifts and demand elasticities for these six crops.

Demand Shift and Elasticity Estimates

Annual data to calculate demand shifts for almonds, mandarins, walnuts, and pistachios were obtained from USDA-ERS. Disappearance was calculated as the sum of domestic consumption plus exports. Annual prices received by growers for corn and soybeans were obtained from USDA-NASS Quick Stats (USDA-NASS, 2020). Disappearance data was obtained from USDA-FAS, again calculated as the sum of domestic consumption plus exports. Annual inverse demand curves from 2000 to 2019 were defined using a constant elasticity function form:

(9) $P = AQ^{\eta_D^{-1}}$

Given a value for the demand elasticity, *A* was solved for at each price-quantity pair and the annual percentage demand change was calculated using equation (4). A demand elasticity that generates demand shifts that are most consistent with whatever market information about the crop is available was used to calculate our final demand shifts.

Here we provide details concerning the information used to calibrate demand shifts and elasticities for corn, soybeans, mandarins, walnuts, almonds, and pistachios. Annual grower-received price data and national disappearance data are used for all crops, which make the resulting demand elasticities those that growers face annually. The data used for calibration include general attributes of the crop, prices of crops that may serve as consumption substitutes, market reports of demand "*sentiment*," production shortfalls of export competitors, shocks to trade policy, and growth of biofuels. We compare our calibrated demand elasticities to notable estimates from the literature when possible. We focus on calibration information since 2000 because we are most interested in demand elasticities that are current enough to be used in forward-looking equilibrium models.

1.4. Calibration of Demand Elasticities for Corn

Corn is used to feed livestock, produce ethanol and food, and as a source for industrial starch. Because corn makes up such a large share of feed, ethanol, and industrial starch markets, there are no close substitutes for corn in terms of another crop being able to cover a significant share of corn use in a single year. Corn is used as a food ingredient in the food market, so its small share of the final cost in producing food products makes the food demand for corn quite inelastic. Although wheat can be used as a feed substitute, almost all livestock feed rations are based off of corn, so it would require wheat to be priced as animal feed rather than human food, and it would require large production increases before wheat could be considered a close substitute for corn. Hence the demand for corn is likely to be inelastic. In addition, the growing share of US corn ending up as ethanol has undoubtedly made corn demand even more inelastic because of government ethanol mandates. Substitution of corn destined for US ethanol plants rather than to relatively-more-elastic export markets would decrease corn's total market demand elasticity.

The most impactful demand shift for corn since at least the 1970s was the 87 million ton increase in corn demand by the US ethanol industry from 2006 to 2010. We use this large increase in demand as our calibration information. One strategy is to solve for the corn demand elasticity that results in an aggregate increase in corn demand of 87 million tons over this period. The resulting demand elasticity is -0.15. However, this assumes that non-ethanol demand stayed constant during this period, which included the great recession of 2009. In addition, distillers' grains, a byproduct of ethanol production, increasingly were used as a substitute feed ingredient which likely negatively impacted the demand for corn as livestock feed.

To see how non-ethanol corn demand changed from 2006 to 2010 is straightforward: simply subtract ethanol use from total use and, conditional on an assumed non-ethanol corn demand elasticity, calculate demand shifts. Figure 3 shows how non-ethanol corn demand changed from 2006 to 2010 for three elasticities, ranging from -1.0 to -0.2. Because corn has such a dominant position in the feed market with no close substitutes, large increases in demand of the type shown in Figure 3 with a demand elasticity of -1 are simply not realistic. The 25% increase in demand in 2007 with the demand elasticity of -0.5 is also likely too large given that US and world livestock numbers did not increase by such a large percentage in a single year. The demand shift pattern with the -0.2 elasticity is more representative of what one would expect. However, non-ethanol corn demand elasticity of -0.2 may be too inelastic given that exports represent approximately 30% of the total non-ethanol demand for corn, and export demand for corn tends to be more elastic. If we sum the total non-ethanol demand shifts over this period for the three elasticities, we obtain the following implications. At a demand elasticity of -1.0, non-ethanol demand increases by 134 million tons or 55% in 5 years. This is not plausible. At a demand elasticity of -0.5, demand increases by 57 million tons or 23%, which may be plausible but not likely given that this period included a recession which negatively impacted feed demand. At a demand elasticity of -0.2, demand increases by less than one ton, which is likely a lower bound. Given these implications, the most likely demand elasticities for non-corn ethanol demand range from -0.4 to -0.3. At -0.4, aggregate demand increases by 39 million tons, or 16%. At -0.3, demand increases by 20 million tons or 8%.

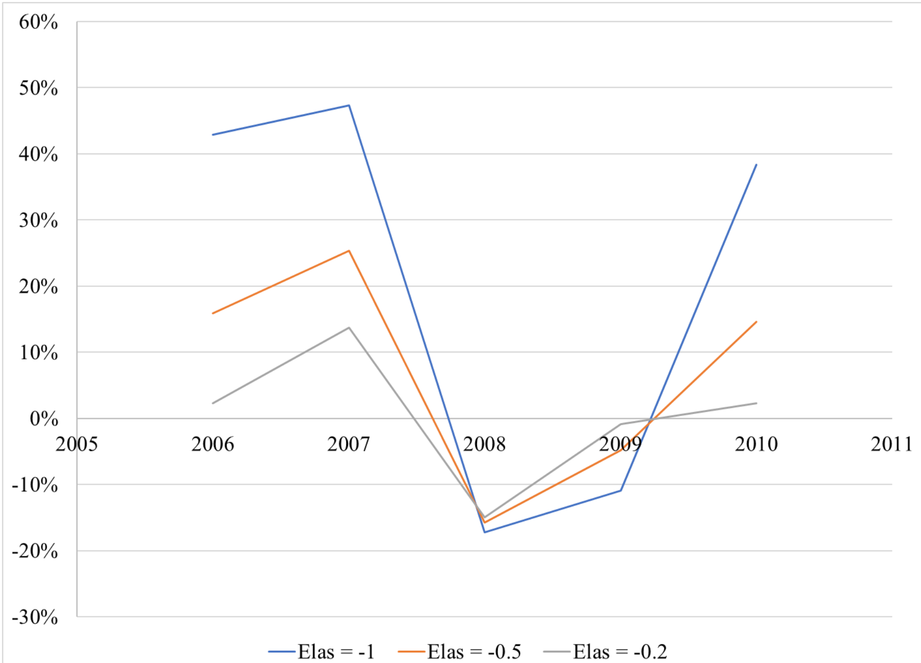

Figure 3. Non-Ethanol Corn Demand Shifts for Three Non-Ethanol Corn Demand Elasticities

We are now ready to calibrate the total corn demand curve. If we add 39 million tons of demand increase for non-ethanol uses of corn to the 87 million ton increase from ethanol over this time period, we get a total demand increase from 2006 to 2010 of 126 million tons. This demand increase is consistent with a total corn demand elasticity of -0.3. A 20 million ton increase for non-ethanol corn demand, which is implied by a noon-corn demand elasticity of -0.3, when added to the 87-million-ton corn demand increase, is consistent with a total corn demand elasticity of -0.23. Thus, we conclude that since 2005, a corn demand elasticity of between -0.2 and -0.3 is most consistent with available market information.

Our calibration estimates of corn demand elasticity are consistent with regression-based results from Adjemian and Smith (2012). They find evidence that increased use of the corn crop to produce ethanol has made corn demand more inelastic, which would be expected given ethanol mandates under the Renewable Fuel Standards. Without accounting for ethanol demand, Adjemian and Smith (2012) estimate a corn demand elasticity of -0.74, which is not consistent with the -0.3 and -0.4 elasticities that we find are most consistent with the demand shift data. But their demand elasticity includes storage demand, whereas we are only interested in corn use demand, so our demand elasticities ought to be more inelastic. Adjemian and Smith (2012) estimate that in low storage years, when the demand elasticity primarily reflects use demand, the demand elasticity is -0.44 without accounting for ethanol use. This demand elasticity is much more consistent with our estimates based on the plausibility of resulting demand shifts. In 2009 and 2010 ethanol production levels Adjemian and Smith (2012) estimate corn demand elasticity of -0.2, which is consistent with our range of estimates

Figure 4 shows aggregate demand changes for corn from 2000 to 2019. The demand elasticity used pre-2005 to calculate these demand shifts is -0.35. The demand elasticity used post-2005 is -0.25 to reflect growing ethanol demand. As shown over these 20 years, corn demand has almost doubled, with an average annual growth rate of 3.51%. However, production over this period did not quite keep up with demand growth, so real prices for corn were a bit higher in 2019 than in 2000.

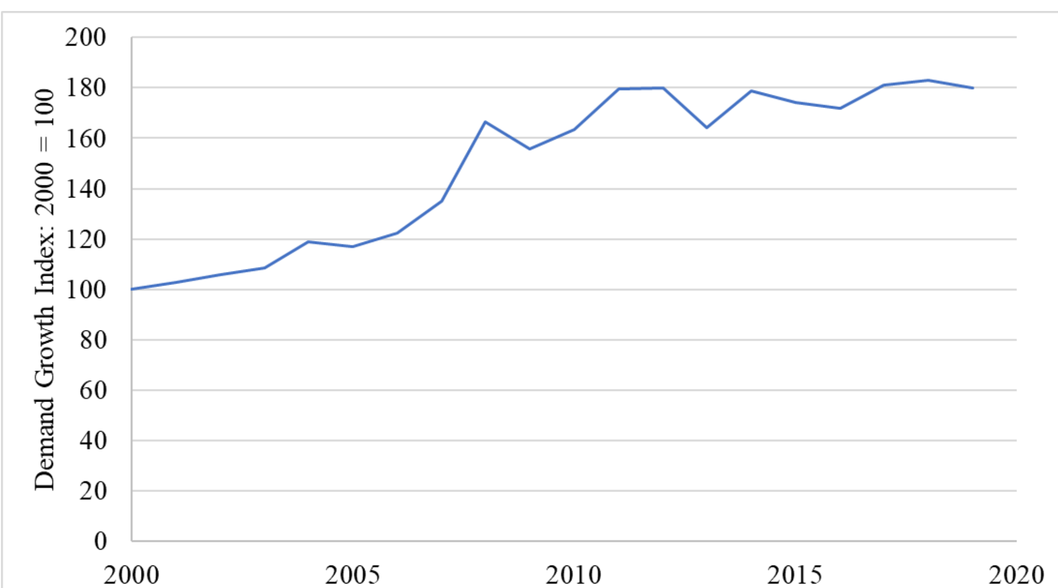

Figure 4. Demand Index for Corn, 2000 =100
Notes: Pre-2005 demand elasticity = -0.35. Post-2004 demand elasticity = -0.25.

1.5.Calibration of Demand Elasticities for Soybeans

The United States and Brazil are the top two soybean producers in the world. When combined with Argentina, South American production far exceeds US production. Because the US exports more than 40 percent of production, competition in export markets increases demand elasticity. But the extent to which export competition increases soybean elasticity is muted to some extent because South American exports largely meet import demand from March to August and the United States meets import demand from September through February.

The demand for soybeans is derived from the demand for soybean meal by the livestock industry and for soybean oil by the biodiesel and food industries. Substitutes for soybean meal include other oilseed meals and distillers' grains. But soybean meal is by far the largest source of protein meal, so substitution is limited. Greater substitution exists for soybean oil because palm oil plays a major role in oil markets. This overview suggests the possibility that total demand for soybeans could be elastic because of competition in oil markets.

Calibration of soybean demand is less straightforward than calibration of corn demand because there are few obvious demand-shifting events that can be identified. Biofuel expansion undoubtedly increased the demand for soybean oil but not soybean meal. To the extent that distillers' grains from ethanol production displace soybean meal in feed rations, it is not clear that expansion of biodiesel resulted in a net increase in demand for soybeans. Figure 5 shows annual demand shifts since 2005 that correspond to three elasticities: -0.2, -0.7, and -1.5.

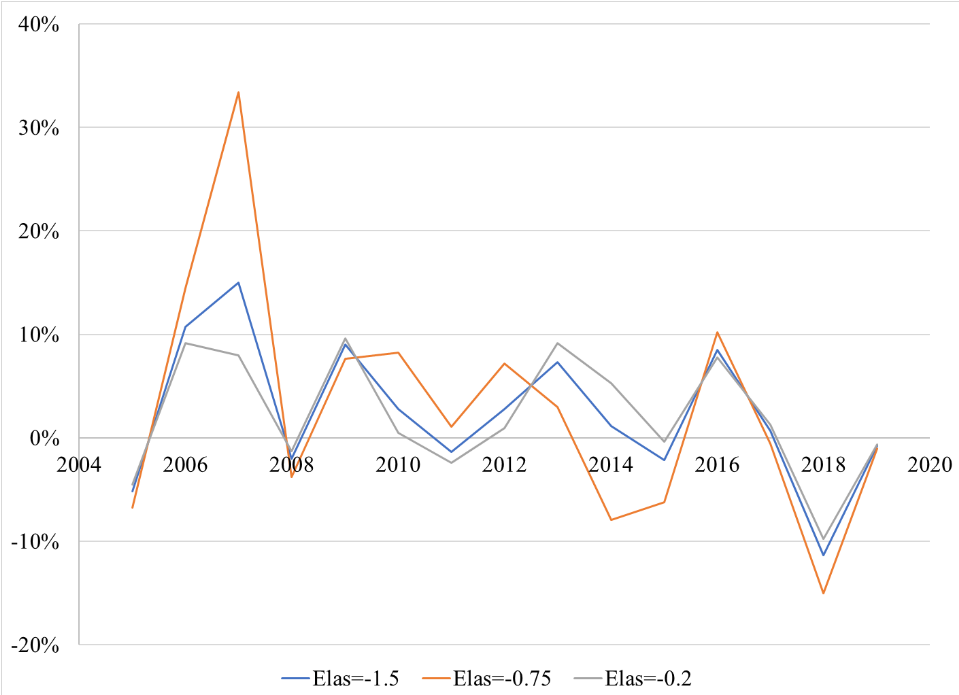

Figure 5. Soybean Demand Shifts Corresponding to Three Demand Elasticities

The difference in estimated demand shifts across the range of elasticities in 2007, 2014, and 2018 may guide which elasticity best aligns with available market information. For example, a soybean demand elasticity of -1.5 implies that demand increased by 87% in 2007. Total soybean used in 2006 was 84 million tons. Total use in 2007 was 83 million tons but at a 57% higher price. Thus, soybean demand increased in 2007, but a demand elasticity of -1.5 implies that had market price increased by 57% in 2007 with no change in demand, then 2007 use would have decreased by 50%. It is not reasonable to conclude that use would have fallen this dramatically given how important soybean meal is to the livestock industry. Furthermore, while 2007 use of soybean oil for biodiesel increased by 36%, this only represents a 5% increase in total soybean oil use. There simply is no support for such a large demand shift implied by a demand elasticity of -1.5. Hence, we can use 2007 to rule out that soybean demand is that elastic.[5]

US soybean exports to China decreased by about 22 million tons in 2018 because of China's retaliatory tariffs imposed on soybeans (See Figure 3 in Adjemian, et al. (2019)). Some shifting of soybean export destinations likely occurred after Chinese soybean tariffs were imposed on US exports, so the 22 million ton decrease in demand for US soybeans likely is an upper limit on the resulting demand shift in 2018, particularly because Chinese pork production would have decreased somewhat anyways in 2018 due to an outbreak of African Swine Fever. This drop in exports represents about 20% of the total use of US soybeans in 2018. The demand elasticity that results in a 22 million ton decrease in soybean demand in 2018 is -0.9. More reasonably, the drop in demand for US soybeans was less than 22 million tons because China purchased more soybeans from Brazil, and some of the unmet demand for Brazilian soybeans likely was met by US soybeans. A more reasonable effect of Chinese tariffs was that US demand for soybeans decreased by something less than 22 million tons. Total US exports decreased by 10 million tons in 2018. Some portion of the difference between 22 and 10 was due to the lower US price of soybeans, and part was likely due to increased demand by countries buying US soybeans instead of Brazilian soybeans. The demand elasticity that corresponds to a 16 million ton decrease in 2018 soybean demand is -0.5, whereas a 13-million-ton decrease corresponds to a demand elasticity of -0.3. Demand elasticity of -0.3 implies a demand shift of 15% in 2007, whereas a -0.5 elasticity implies a much larger shift of 23%. As discussed above, soybean demand increased in 2007, but no significant event can be identified to justify a large increase in

[5] The large price increase in 2007 was likely a supply side shock caused by increased demand for corn. Without a corresponding increased soybean price many more acres of corn would have been switched out of soybeans. An inelastic demand for soybeans prevented much of this shift from happening.

demand. Combining the pattern of demand shifts shown in Figure 5 with the information about the drop in demand caused by the 2018 trade war leads us to conclude that soybean demand is inelastic during this period, with a demand elasticity less than -0.5. Figure 6 shows the index of soybean demand corresponding to a demand elasticity of -0.35. Demand has increased by about 50% in aggregate over this period, whereas production has about doubled. This divergence between demand and supply growth has led to a large reduction in real soybean prices since 2000.

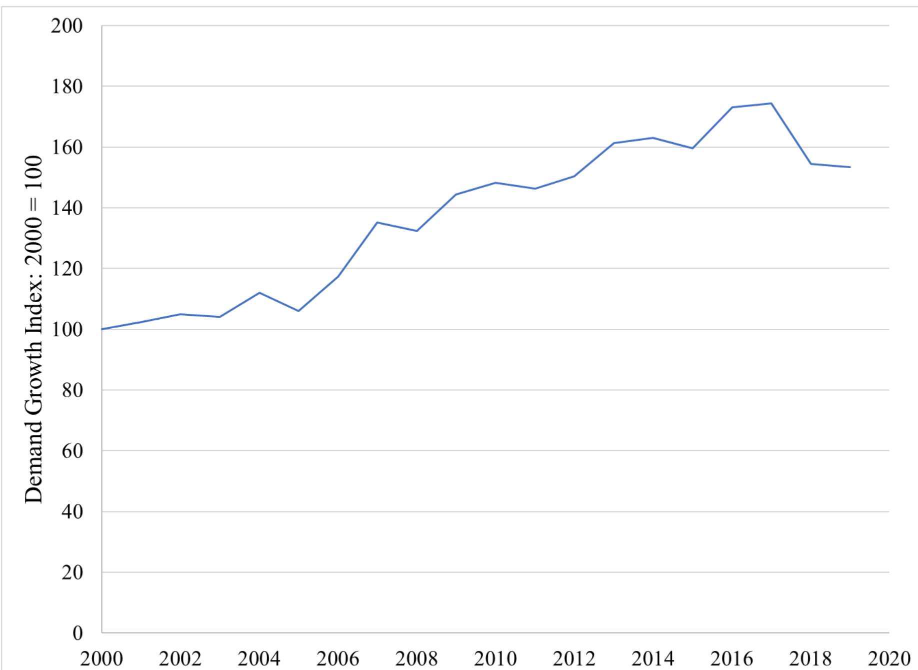

Figure 6. Demand Index for Soybeans, 2000 = 100

1.6. Calibration of Demand Elasticities for Almonds

Figure 7 shows almond demand shifts for three elasticities ranging from -1.0 to -0.2. A more elastic demand elasticity was not considered initially based on prior estimates of demand elasticity (Russo, et al., 2008). However, these prior demand elasticities were estimated using data only up to 2001. US almond production since then has tripled. In addition, new uses of almonds as a dairy substitute have been developed since that time. Our focus, therefore, is on the post-2000 period in Figure 7.

The most significant differences in demand shifts between the different elasticities in Figure 7 are the two years of 40+% demand increases in 2002 and 2003, the three consecutive years of demand decrease from 2006 to 2008, and the large demand decrease in 2015 and 2016 at the demand elasticity of -1. Such large demand swings are consistent with almonds having a close substitute and a subsequent elastic demand. In addition, the prices of these substitutes must move in the same direction as the demand shifts and be large enough to have the implied effect on demand. Two candidate substitute products are walnuts and pistachios. In 2002 the price of pistachios increased by 7%, and the price of walnuts increased by 3%. In 2003 the price of pistachios increased by 8%, and the price of walnuts decreased by 3%. Although the sign of 3 out of the four price movements was in the correct direction to explain demand increases for almonds, the magnitude of the price movement seems not large enough to cause the implied demand shifts unless the goods are nearly perfect substitutes. But if they were perfect substitutes, then the demand elasticity for almonds would be much more elastic than -1. So, increases in the price of pistachios and walnuts could have contributed to demand increases in 2002 and 2003 but cannot explain the large implied changes with a demand elasticity of -1.

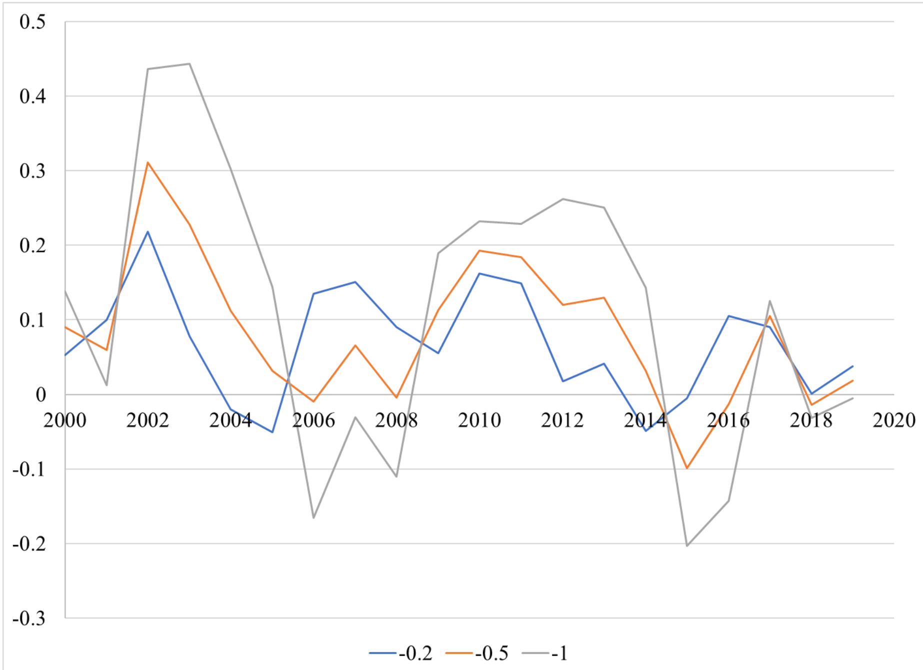

Figure 6. Sensitivity of Almond Demand Shifts on Demand Elasticity

In 2006, 2007, and 2008, the price of walnuts did not change, increased by 36%, and then decreased by 46%, respectively. On the other hand, the price of pistachios fell by 10%, fell by 27%, and increased by 40% in these years. Again, this price change pattern cannot readily explain why almond demand should have decreased during these years, as implied by a demand elasticity of -1. Thus, our focus is on finding market information that allows for the calibration of a more inelastic demand.

Turning to 2015, prices fell by 22%, yet use only increased by 3%. If there were no shifts in demand, then the demand elasticity is -0.15. Market reports[6] about the first half of the marketing year indicate "soft global demand" for almonds. Part of the softness seems to have been reluctance by buyers to continue buying the same amount of almonds at the previous year's price, which indicates that demand decreased. If we conclude that there was indeed a demand decrease in 2015, then demand is more elastic than -0.15.

[6] For example, see here: https://www.recordnet.com/article/20160323/NEWS/160329876

Market observers before the 2016 marketing year predicted a more stable marketing environment. But 2016 production increased by 13%, and use subsequently increased by 10%. Almond prices dropped by 25%. Market reports indicate stable demand in 2016[7] and the ability to market more almonds because of a lower almond price. The demand elasticity that implies no demand shift in 2016 is -0.45. No market reports indicate a decline in demand relative to 2015. Rather, the market commentary suggests strong export demand and increased domestic consumption. But at least some of this market sentiment could have resulted from movement along the demand curve caused by lower prices. We conclude that the almond demand elasticity falls in the range between -0.15 and -0.45. The lower bound of this range is consistent with no demand changes in 2015, a year in which market commentary revolves around weak demand. The upper limit of -0.45 would apply if there were no demand change in 2016, a year in which market commentary suggests demand increased. A demand elasticity at the more inelastic part of this range is consistent with limited substitution between almonds and other nuts, while a demand elasticity towards the more elastic part of the range indicates greater substitution possibilities. Given the market commentary about the advantage a lower almond price gives almonds relative to other tree nuts, the elasticity of -0.4 seems most consistent with available market information. In particular, a demand elasticity of -0.4 implies that demand decreased 7.6% in 2015 and increased by 1.5% in 2016, both of which are consistent with available market commentary. Figure 7 shows the resulting index of almond demand since 2000. Demand has grown by an average of 8% annually since 2000.

[7] https://bluediamondgrowers.com/grower-news/almond-market-update/

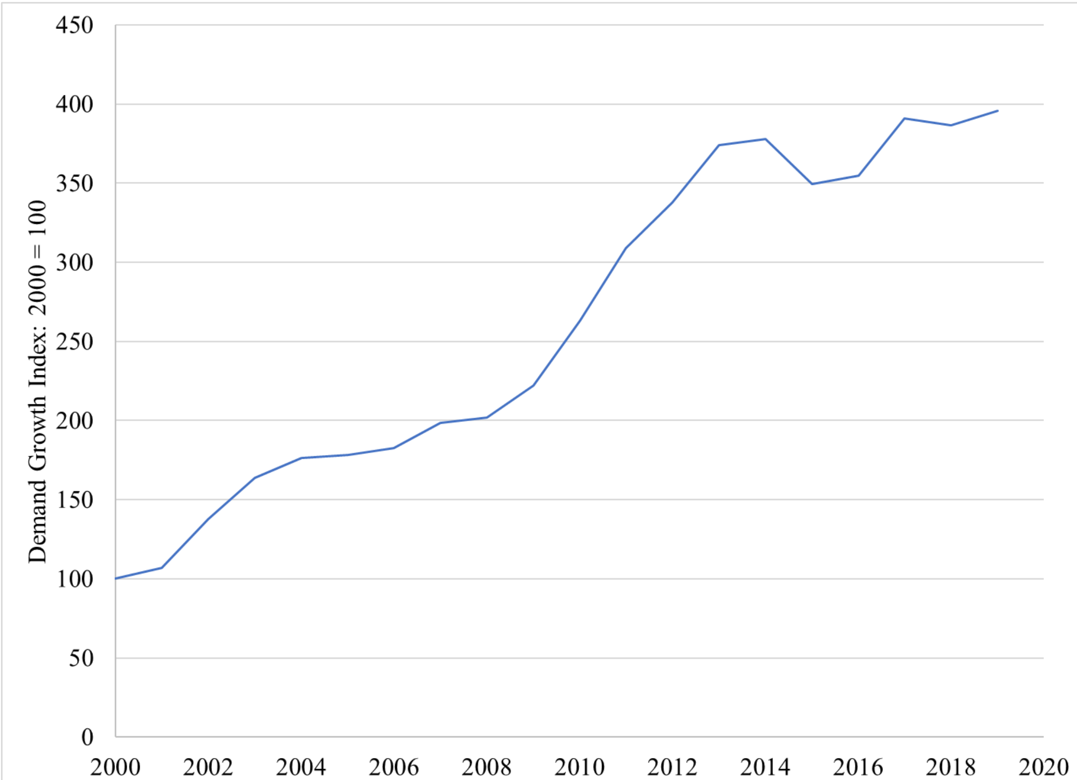

Figure 7. Market Demand Index for Almonds with a Demand Elasticity of -0.4

1.7.Calibration of Demand Elasticities for Mandarins

Figure 8 shows three demand shift patterns for mandarins from 2000 to 2019 corresponding to three alternative demand elasticities ranging from quite inelastic to elastic: -0.2, -0.7, and -1.5. We chose an initial wide range of elasticities because we found no estimates of mandarin demand elasticity in the literature. The pattern and magnitude of the corresponding demand shifts give insight into which demand elasticities are most consistent with the data. Demand elasticity of -1.5 results in much larger annual variations in estimated demand than the other two elasticities. If mandarin demand elasticity is -1.5, then mandarin demand increased by 45% in 2013, decreased by 30% in 2014, increased by 50% in 2015, decreased by -20% in 2016, and increased by 30% in 2017. One possible explanation for such large annual swings in demand would be a close substitute for mandarins, which makes its demand elastic. However, the relative price of the substitute would need to have increased dramatically in 2013, 2015, and 2017 and decreased in 2014 and 2016. Candidate substitute products would be products that buyers turn to if their price fell relative to mandarins and would turn away from when their price rose relative to mandarins. One obvious candidate product would be navel oranges. But the relative price of navel oranges decreased by 38% in 2015 and increased by 33% in 2016. This would have the effect of decreasing demand for mandarins in 2015 and increasing demand in 2016. The relative price of apples to mandarins fell by 8% in 2015 and by another 5% in 2016, a pattern that cannot explain such large variations in annual mandarin demand if demand elasticity is -1.5.

Large demand shifts for mandarins are certainly possible. For example, in 2009, the quantity of mandarins purchased in the United States increased by 32% even though the grower price increased by 12%. This is clear evidence that demand increased by more than 32% in a single year. The magnitude of the 2009 demand increase varies somewhat across the three demand elasticities, but the fact that demand increased significantly is not in question.

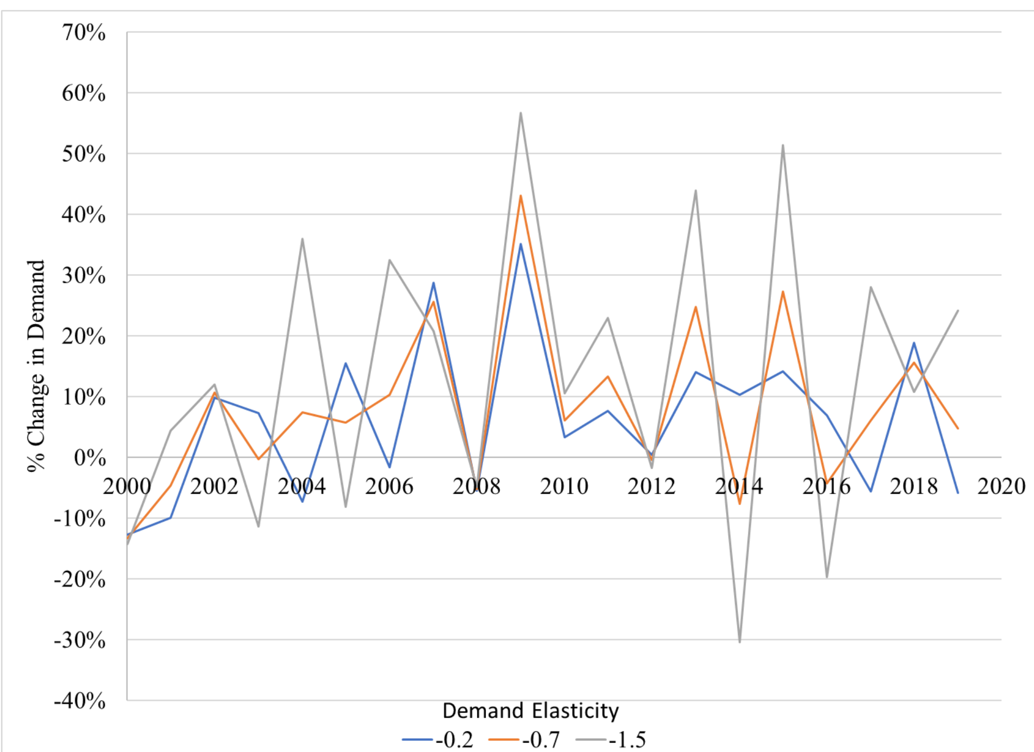

Figure 8. Annual Shifts in Mandarin Demand Corresponding to Three Elasticities

It is not reasonable to see large annual fluctuations in US domestic demand for mandarins, as shown in Figure 8 from 2013 to 2017 unless a close substitute with a relative price rose and fell in exactly the required pattern. A search for such a close substitute bore no fruit. Hence, we judge the demand elasticity for mandarin at the farm level to be much less elastic than -1.5 certainly. Demand elasticity of -0.2 implies much more consistent growth over time, but products with such an inelastic demand would tend to have very few substitutes in the market, which is not the case for mandarins, given the variety of fresh fruits available. Thus, we judge the elasticity of grower-level demand for mandarins to be between -0.3 and -0.7. Figure 9 shows the pattern of demand shifts with these three elasticities.

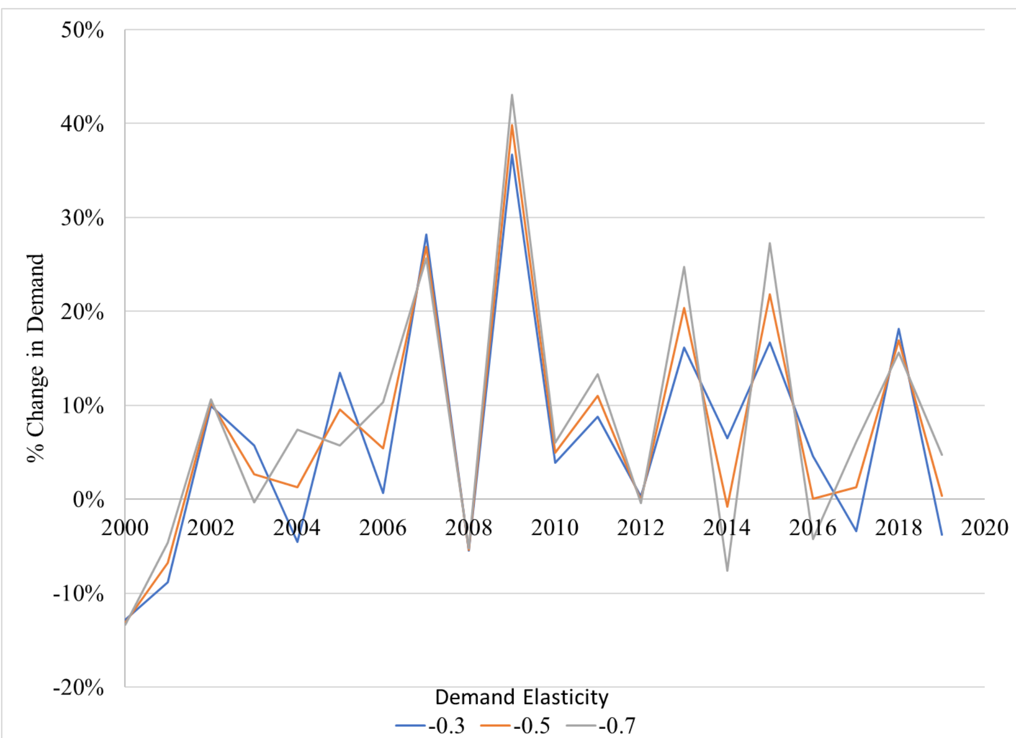

Figure 9. Sensitivity of Annual Mandarin Demand Shifts to Inelastic Demand Elasticities

The resulting growth over time since 2000 in demand for mandarins for these three demand elasticities is shown in Figure 10. Demand shift estimates across the three elasticities are similar with the exception of 2014, where the less inelastic demand elasticity implies a demand drop rather than no change or a demand increase. As shown in Figure 10, demand growth has been rapid since 2000 when the seedless Tango variety became more widely available. Demand growth since 2000 with the -0.5 demand elasticity averaged 7.8%. Total use over this period has grown by an average of 5.7%, indicating that real prices for mandarins should have increased over this period. And, indeed they have, growing by approximately 3.7% per year. As shown in Figure 10, a more elastic demand implies somewhat greater demand growth, implying greater real price growth. But a more elastic demand also implies a greater response of quantity demanded to those high prices, which reconciles the greater wedge between estimated demand growth and real price increases at the more elastic demand.

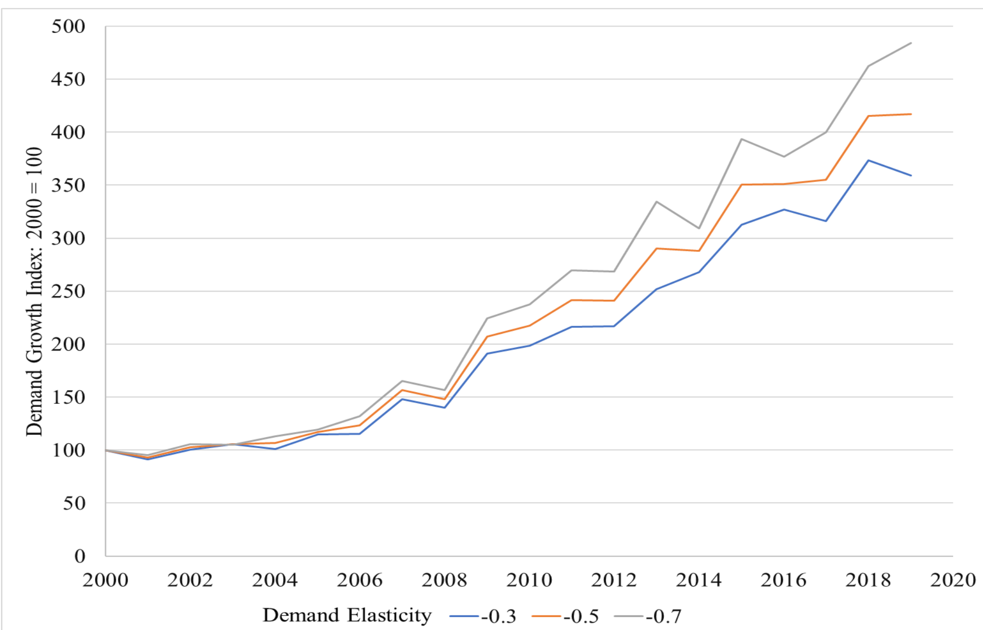

Figure 10. Demand Growth Indices for Mandarins for Alternative Demand Elasticities

1.8. Calibration of Demand Elasticities for Pistachios

As with mandarins, we found no published demand elasticity estimates, so we begin by looking at demand shifts (Figure 11) implied by a wide range of elasticities: -2, -1, -0.5, and -0.2. The more elastic demands are consistent with pistachios having close substitutes products, which would likely be other nuts such as almonds and walnuts. The more inelastic estimates are consistent with less substitution and pistachios purchased as a food ingredient necessary to a final product.

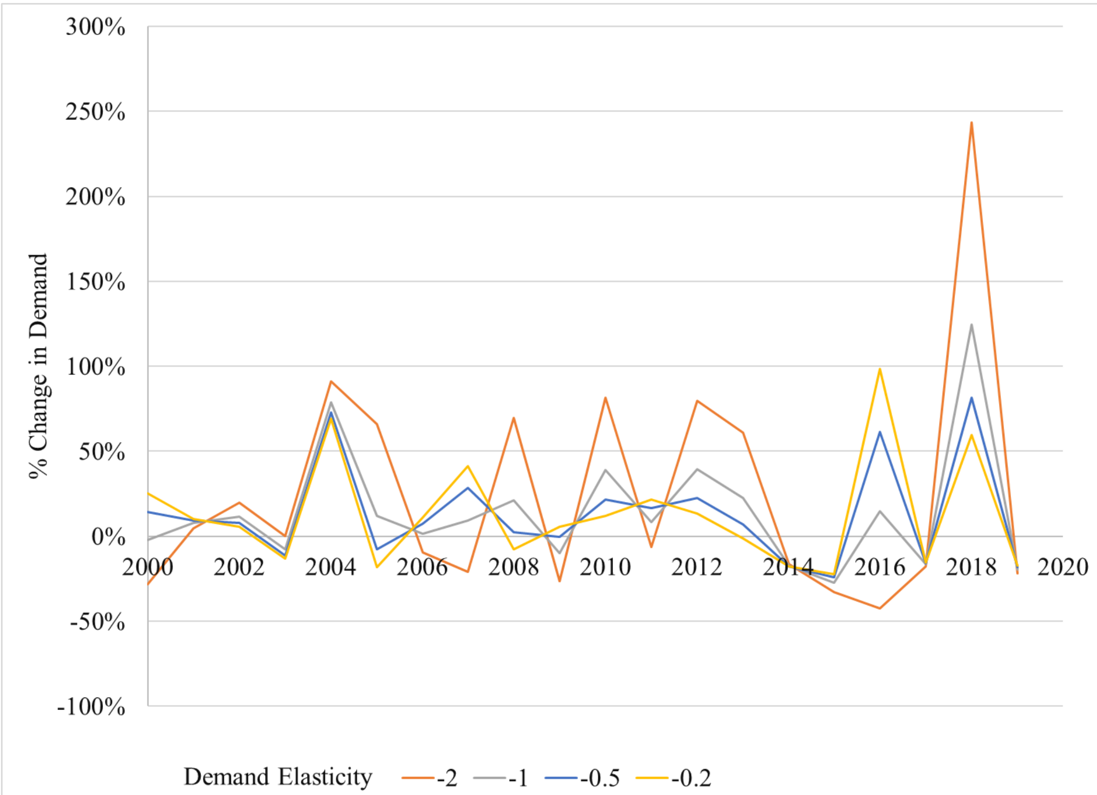

Figure 11. Demand Shifts for Pistachios for Different Demand Elasticities

The difference in demand shifts across the four elasticities provides calibration opportunities. In 2016, a demand elasticity of -2 implies that demand dropped precipitously, whereas an elasticity of –0.2 implies that demand doubled. All elasticities showed very strong demand growth in 2018, but if pistachio demand is quite elastic, demand increased by 250% in 2018. We first focus on 2016 to determine whether demand for pistachios is likely to be quite inelastic.

Pistachio disappearance more than doubled in 2016 from 74 to 169 thousand tons. This increase was facilitated by US production increasing from 61 to 202 thousand tons. The grower price of pistachios fell by 50%. If there were no demand shifts in 2016 and all the increased use was movement along the pistachio demand curve, then the implied demand elasticity facing growers is -1.2. A more elastic demand implies a large decrease in demand in 2016, and a more inelastic demand suggests a large increase in demand. The price of almonds fell by 25% in 2016, which would result in increased demand for pistachios if the two nuts are substitutes.

On the other hand, walnut prices increased by 10% in 2016, decreasing pistachio demand if the two nuts are substitutes. But we conclude walnut demand is quite inelastic, so it is difficult to make the case that walnut prices significantly influence pistachio demand. Thus, consideration of prices of substitute nuts supports the idea that demand increased in 2016 so that the demand elasticity is less elastic than -1.2.

Total world exports increased significantly in 2016, likely in response to lower prices but also likely due to continued world demand growth. Exports increased by about one-third, indicating that total export demand is inelastic—given the 50% drop in price—particularly given evidence of continued demand growth in export markets. In 2018 all demand elasticities implied a large increase in pistachio demand of at least 50%. The reason for this agreement between the elasticities is that pistachio use increased by almost 50% even though the price increased by more than 50%. The source of this demand increase was not an increase in the price of either almonds or walnuts because both prices fell in 2018.

Turning to exports first, export demand for US pistachios increased in 2018 because Iranian production levels were down 66% (Iran accounted for 35% of world production in 2017)[8]. This drop in production reduced Iranian exports by about 51 thousand tons. Total world trade decreased by about 13 thousand tons[9] presumably because of sharply higher pistachio prices. US exports increased by 32 thousand tons in 2018. The gap between the drop in Iranian exports and the increase in US exports is largely accounted for by increased exports from Turkey

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[8] https://www.wcngg.com/2019/09/16/pistachio-prices-hinge-on-export-expectations/

[9] https://downloads.usda.library.cornell.edu/usda-esmis/files/tm70mv16z/5d86ps499/w9505t77g/TreeNuts.pdf

and the drop in world trade. If market prices had remained unchanged and US supplies were sufficient, then it is likely that US exports would have increased in 2018 by about the same amount that Iranian exports dropped. That is, the drop in Iranian exports provides a reasonable measure of the export demand increase faced by US growers in 2018. We can conclude that if pistachio export demand were elastic, then the 50% increase in 2018 prices would have resulted in a much larger drop in aggregate world imports. That imports only decreased by 7% when the price increased by 50% indicates that total import demand is quite inelastic. Because the US exports 50% more pistachios than it consumes domestically and is the world's largest exporter mean that a large part of total US demand for pistachios is inelastic. It is notable that in 2019, a year in which grower prices decreased by a scant 3%, Iranian exports rebounded by 54 thousand tons, and US exports dropped by 45 thousand tons. Total world exports in 2019 remained only 5% lower than 2017 levels despite prices being 50% higher.

Turning to domestic demand, a simple examination of the 2015 and 2016 data indicates that domestic demand for pistachios is elastic. Per-capita consumption in 2016 increased from 0.23 to 0.43 pounds per person the same year in which grower prices dropped in half. However, this sharp increase in domestic consumption was not caused by price alone because in 2018 and 2019, grower prices were 42% higher, but per-capita consumption *increased* to 0.54 pounds per person in 2019. Thus, we cannot conclude from the 2015 to 2016 arc elasticity that domestic demand is elastic. Instead, we conclude that demand growth for pistachios continues to occur and the sharp increase in 2016 was a coincidence of response to price and demand growth. Evidence for an elastic domestic demand would be consistent positive movements between shifts in demand and prices of substitute products, such as almonds and walnuts; movements which do not find.

The above discussion supports an inelastic demand for pistachios. Although it appears that export demand is quite inelastic, robust market competition with Iran, which has a 44% market share of world exports in 2019 compared to the 52% share for the United States, suggests that current export demand facing US growers is not too inelastic. In addition, it is likely more than a coincidence that US per-capita consumption of pistachios increased so dramatically in the same year that price fell in half. Figure 12 shows aggregate demand growth for pistachios since 2000 with a demand elasticity of -0.5. The average annual demand growth has been 9.4% since then. A more inelastic demand of -0.3 implies that demand growth has been 8.8%. A more elastic demand of -0.7 implies 10% annual growth.

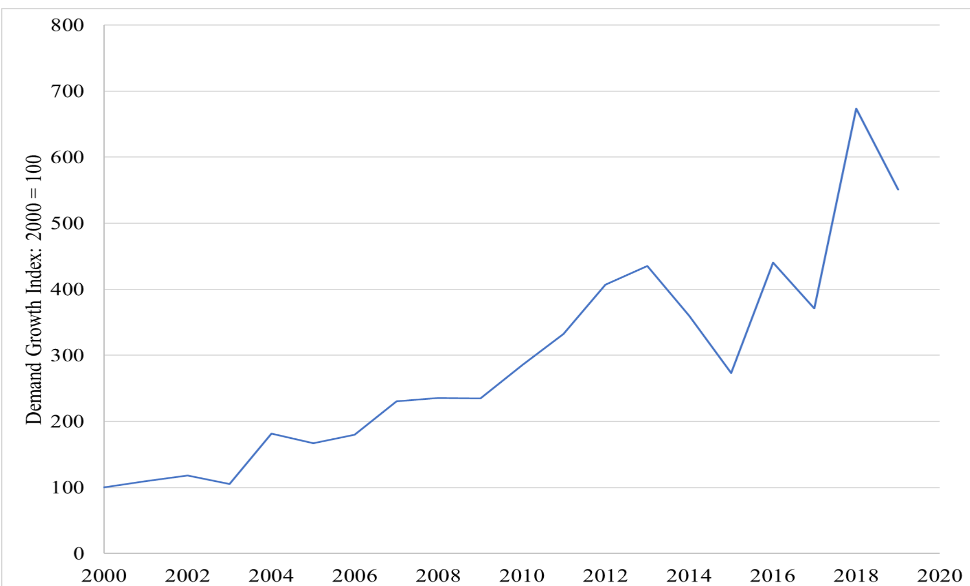

Figure 12. Market Demand Index for Pistachios with a Demand Elasticity of -0.5

1.9.Calibration of Demand Elasticities for Walnuts

Using data from 1970 to 2001, Russo, et al. (2008) estimated that US walnut growers' total market demand elasticity was extremely inelastic after 1983 at -0.061. But the market for walnuts has dramatically changed since this estimate was published in 1983. Exports made up 22% of total demand, whereas, in 2019, exports make up 67% of a much larger market. Export demand tends to be more elastic than domestic demand because products from other countries are close substitutes for US walnuts. However, the US remains the world's dominant walnut exporter with a 50% market share of the world export market. Figure 13 shows the pattern of demand shifts for walnuts for three candidate demand elasticities.

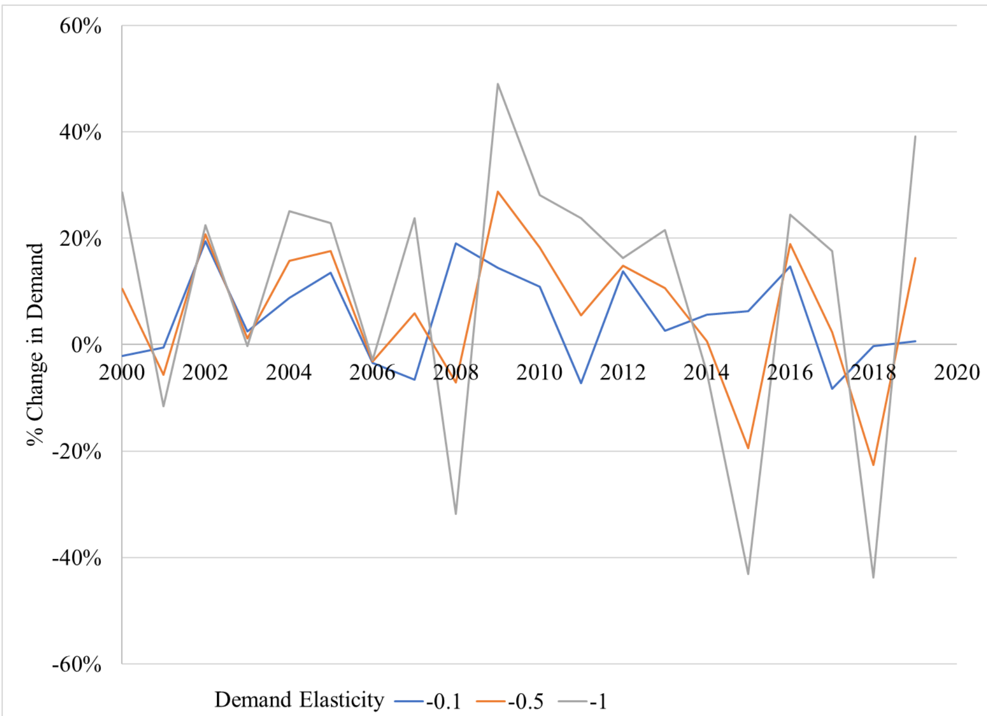

Figure 13. Annual Shifts in Walnut Demand Corresponding to Three Elasticities

A pattern of wide annual swings in demand with a more elastic demand is again evident, with particularly sharp demand decreases in 2015 and 2018 and a large increase in 2019. Examining large supply changes among competitors in the world export market cannot explain such large variations. In 2019 China had a bumper crop while Chile had a bit of a short crop. The net effect of these two competitors should have been a slight demand decrease in 2019, not an increase. In 2018 exports from Chile increased but so too did the aggregate export market. In 2015 there were no evident supply shortages among US export competitors. The other explanation for large demand decreases in 2015 and 2018 could be dramatic relative price decreases for a substitute product, such as almonds. But the relative price of almonds increased dramatically in both 2015 and 2018. If walnut and almonds are close substitutes, which makes for a more elastic demand, walnut demand should have increased in 2015 and 2018. Because the demand shift patterns with the demand elasticity of -0.5 are so similar to the patterns with a -1.0 elasticity, a pattern for which we can find no justification, we conclude that demand shifts that correspond to a quite inelastic demand are most consistent with available market information. Figure 14 shows the resulting demand growth indices for walnuts for demand elasticities of -0.1, -0.2, and -0.3.

Demand growth for walnuts from 2000 to 2019 at a demand elasticity of -0.2 averaged 3.2% annually. The estimated aggregate shift in demand for walnuts from 2000 to 2019 at all three demand elasticities was about 160,000 metric tons which almost exactly matches the increase in consumption of US (California) walnuts. Thus, inflation-adjusted walnut prices in 2019 are approximately equal to what they were in 2000. Because California produces practically all US walnuts, California acreage growth has kept pace with demand growth over this period, increasing by an annual rate of 3.2%. Real prices in 2019 are down by about 50% since their peak in 2012-2014, mostly because of rapid acreage growth of 4.4% since 2013.

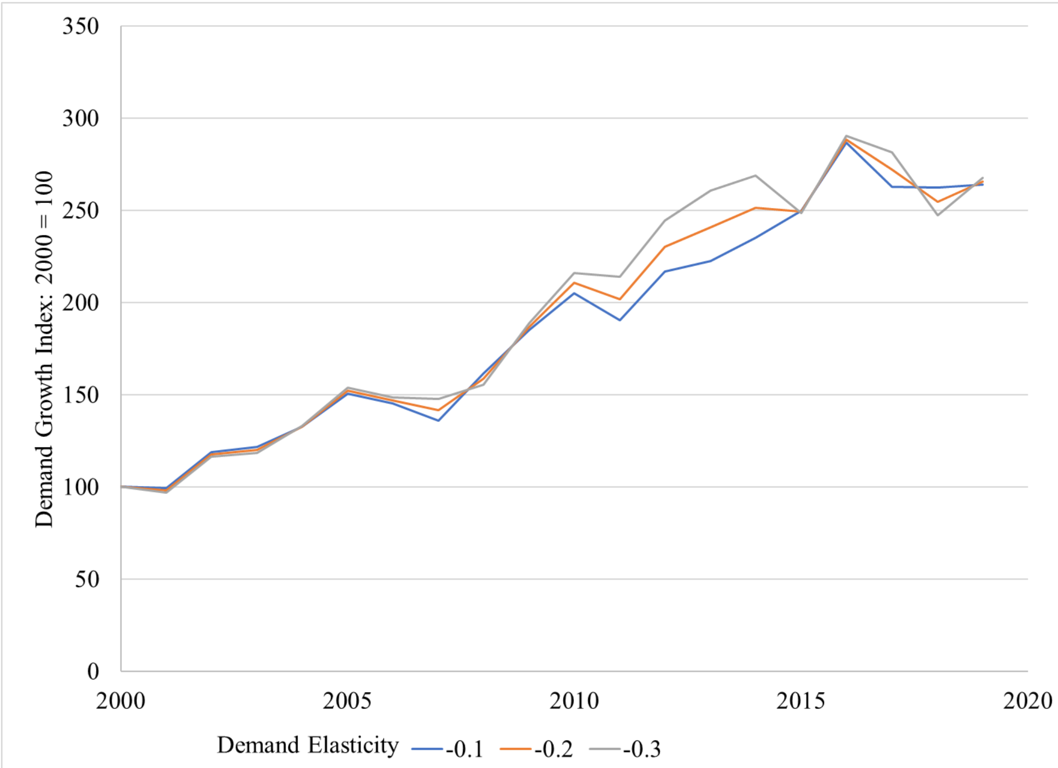

Figure 14. Demand Growth Indices for Walnuts for Alternative Demand Elasticities

1.10. Most Likely Demand Elasticities and Demand Shift Estimates

Table 2 summarizes ranges of grower-level calibrated demand elasticities for all six crops in the study and the authors' judgment using market information presented above on the most likely elasticity. Notably, demand for all these crops is inelastic.

Table 2. Calibrated Elasticity of Demand for study Crops.

Crop	Calibrated range	Most likely
Corn*	[-0.40, -0.20]	-0.25 & -0.35
Soybeans	[0, -0.50]	-0.35
Almonds	[-0.15, -0.45]	-0.40
Mandarins	[-0.30, -0.70]	-0.50
Pistachios	[-0.30, -0.70]	-0.50
Walnuts	[-0.10, -0.3]	-0.20

Source: Calculated by authors.
Notes: For pre-ethanol, the most likely elasticity range for corn is between -0.30 and -0.40, and since 2005, a corn demand elasticity of between -0.20 and -0.30 is most consistent with available market information.

Using the most likely demand elasticities for each crop (Column 3 in Table 2), we calculated the annual demand shifts for each crop (Table 3). As indicated in this table, average annual demand shifts vary quite a bit across crops. For example, pistachio demand has increased on average by almost 13% from 2001 to 2019. Almond demand has increased by 7.8%, whereas walnut demand has increased by a relatively modest 5.6%, on average. Corn and soybean demand have grown much more slowly over this period at 3.1% and 2.5% average annual growth rates.

Table 3. Demand Elasticities and Annual Demand Shifts for Five Crops since 2000

	Corn	Soybeans	Almonds	Pistachios	Walnuts	Mandarins
2001	0.030	0.023	0.070	0.092	-0.019	-0.068
2002	0.024	0.027	0.287	0.080	0.198	0.103
2003	0.094	-0.009	0.188	-0.111	0.022	0.026
2004	-0.015	0.075	0.077	0.729	0.105	0.013
2005	0.046	-0.052	0.010	-0.079	0.145	0.095
2006	0.104	0.107	0.025	0.075	-0.034	0.054
2007	0.232	0.150	0.087	0.284	-0.036	0.269
2008	-0.065	-0.020	0.019	0.024	0.119	-0.054
2009	0.050	0.090	0.099	-0.005	0.179	0.398
2010	0.098	0.028	0.185	0.215	0.127	0.049
2011	0.003	-0.014	0.175	0.166	-0.042	0.110
2012	-0.089	0.028	0.093	0.226	0.141	-0.001
2013	0.089	0.073	0.107	0.070	0.046	0.203
2014	-0.025	0.011	0.011	-0.175	0.044	-0.008
2015	-0.012	-0.022	-0.076	-0.240	-0.009	0.218
2016	0.053	0.085	0.015	0.614	0.158	0.001
2017	0.010	0.007	0.102	-0.158	-0.057	0.013
2018	-0.017	-0.114	-0.010	0.814	-0.064	0.169
2019	-0.026	-0.007	0.023	-0.181	0.043	0.004
Average	**0.031**	**0.025**	**0.078**	**0.128**	**0.056**	**0.084**

Figures 15 and 16 show demand indices (index = 100 in the year 2000) of demand changes from 2000 to 2019. Over this period, almonds demand has grown by 7.3% annually; pistachios by 9%; mandarins by 8.84%; walnuts by 5.78%; whereas corn and soybean demand have grown by 3.51% and 3.02% annually, respectively. The increased demand for corn and soybeans by the biofuel industry is easily seen by the relatively rapid demand growth from 2003 to 2010 (average growth of 4.2% for corn and 4.1% for soybeans). The overall demand growth for both crops has been remarkably similar and highly correlated, a topic we will return to when estimating supply elasticities.

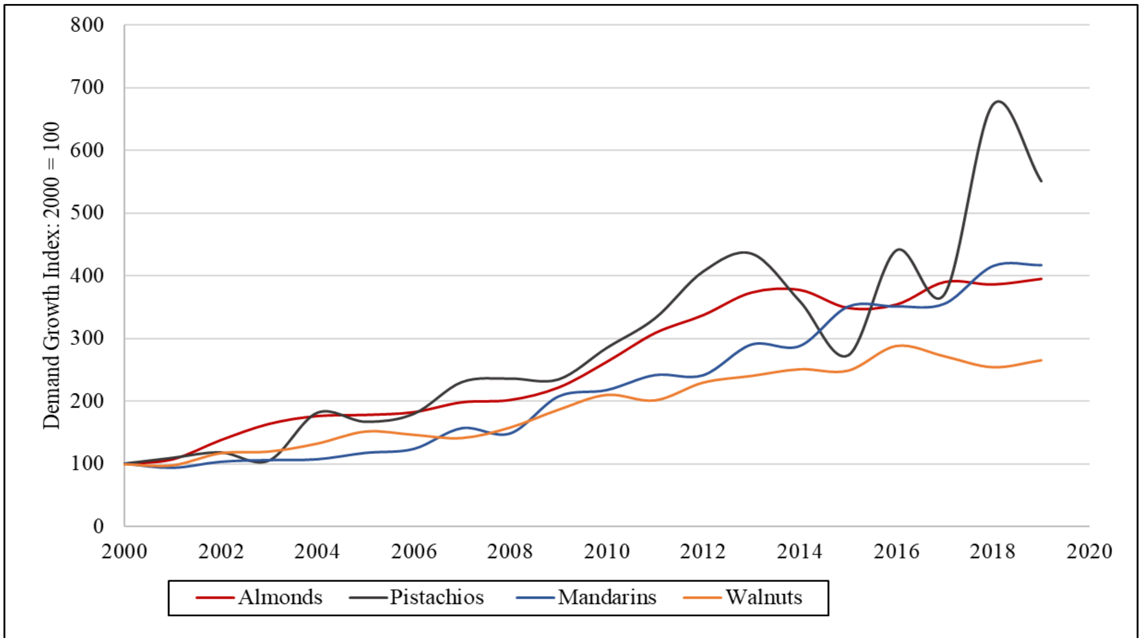

Figure 15. Demand Index for Almonds, Pistachios, Mandarins, and Walnuts
Source: Calculated by authors from Table 3 results.

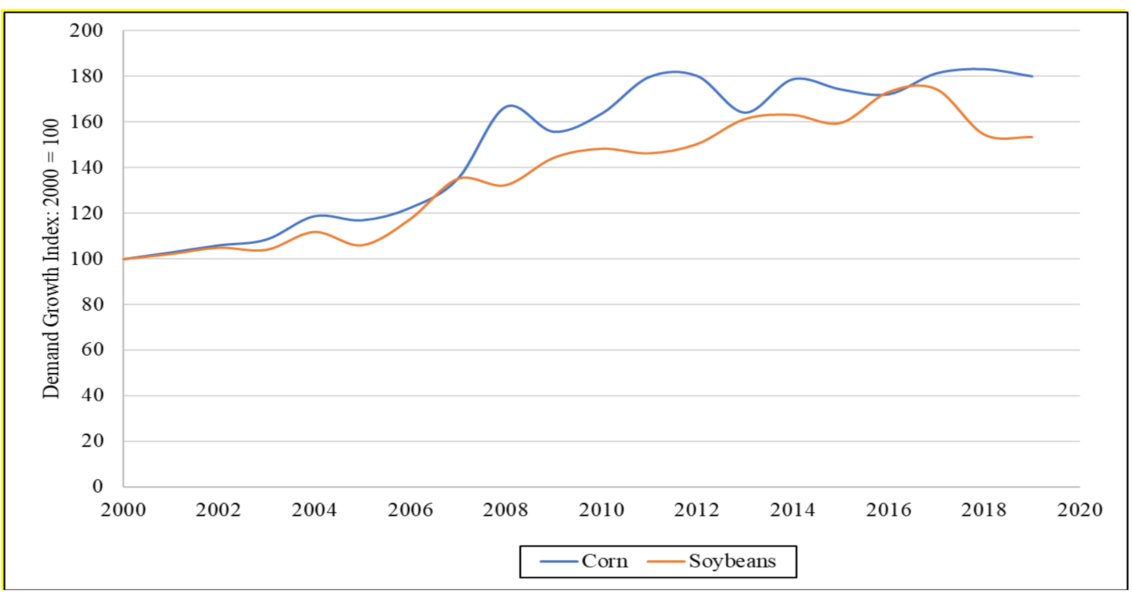

Figure 16. Demand Index for Corn and Soybeans
Source: Calculated by authors from Table 3 results.

Supply Elasticities Estimates

We now turn to using our estimates of demand shifts to estimate supply elasticities. The first step is to estimate acreage response to demand shifts using demand shifts calculated above and total bearing planted acreage. The change in acreage estimation uses national-level time series annual data on total bearing planted acreage and demand shifts, between 2000 and 2019, for corn, soybeans, and tree crops including almonds, mandarins, pistachios, and walnuts in the US. The total annual bearing planted acreage at the national level was obtained from USDA-NASS (USDA-NASS, 2020).

We estimate a regression model using annual level data on bearing planted acreage and calculated demand shifts. The base equation we estimate is reported in equation (10):

(10) $$\ln(A_t) = \alpha + \gamma \ln\left(DS_{t-j}\right) + u_t$$

where A_t is the total bearing planted acreage in the US at year t; DS_{t-j} is the lag demand shift in year *t-j*; and u_t captures all unobserved factors affecting the dependent variable. Equation (10) will be estimated separately for all six crops in this paper. Before estimating the acreage response, we need to address the issue of the time lag between when a demand shift occurs and when the resulting supply response will show up in the data.

1.11. Discussion of Number of Lags on Demand Shift Used to Identify Bearing Acreage Response

The time lag between demand shifts and bearing acreage changes needs careful consideration. Tree crops take multiple years before they bear production. Bearing acreage is the most typical way that acreage is reported, so a change in bearing acreage occurs in response to decisions made three to six years previously, depending on the crop. Previous studies indicate that almonds and mandarins in California do not bear significant fruit during the first 3 to 4 years after planting (Boriss and Brunke, 2005, Etaferahu, et al., 2005, Haviland, et al., 2019, Jarvis-Shean, et al., 2018, Lampinen, et al., 2006, Micke, 1996). Pistachios also have a significant lag between the planting year and bearing year. Pistachios in California start bearing in years 5-6 and reach full production by nine and beyond (Baldwin, et al., 2020, Ferguson and Haviland, 2016, Kallsen and Parfitt, 2008). Walnuts start bearing in years 4-5 and reach full production by year 8 (Buchner, et al., 1995, Buchner, et al., 2002, Grant, et al., 2017, Jarvis-Shean, et al., 2018).

United States Department of Agriculture (USDA) National Agricultural Statistics Service (NASS) defines bearing age as when trees can normally be expected to produce a commercially significant quantity of the crop. Bearing age is a function of many factors, including climate, variety and rootstock. USDA-NASS defines almonds bearing acreage as plantings four years and older, mandarins bearing acreage as land planted with citrus trees of at least three years of age, pistachios bearing acreage as plantings six years and older, and walnuts bearing acreage as plantings between 4-7 years and older depending on the variety (USDA-NASS, 2001, USDA-NASS, 2019, USDA-NASS, 2020, USDA NASS, 2012).

As discussed above, annual crop data is most often reported by the marketing year. So, for example, a U.S. corn crop planted in April of year t, cannot respond to a demand increase calculated from data generated in marketing year t because the marketing year begins in September of year t in most producing regions. An April-planted crop is only 2/3rds of the way through the t-1 marketing year, suggesting that a two-year lag between demand shifts and acreage changes may be most appropriate.

To address the lag between planting and bearing, we use the average demand shift in years t-4, t-5, t-6 to estimate the response in planted bearing acreage in year t for all tree crops based on farmers likely using the demand shifts from the previous periods to inform current planted bearing acreage. We use average demand shift in years t-1 and t-2 to estimate the response in planted acreage for corn and soybeans. We take an average of demand shifts to account for transitory demand shifts such as those caused by production shortfalls in an export-competing country. In addition, we consider two alternative models to assess the robustness of the results. For our first robustness test, for the tree crops, we use average demand shifts in years *t-3*, *t-4*, and *t-5,* and for corn and soybeans, we only use demand shifts in year *t-2*. As a second robustness check, following studies indicated above, we estimate our modeling using a four years lag for mandarins, five-period lag of our demand shift measure for almonds and walnuts, six years for pistachios, and one year for corn and soybeans.

1.12. *Estimation of Acreage Response*

The results of the acreage change estimation based on equation (10) are presented in Table 4. This table uses the average demand shift in years *t*-4, *t*-5, *t*-6 to estimate the response in planted bearing acreage in year *t* for all tree crops and average demand shift in *t*-1, *t*-2 to estimate the response in planted acreage in year *t* for corn and soybeans. The estimated elasticity of acreage with respect to demand shifts (γ) for pistachios is the largest (most elastic) among these crops (0.73), followed by mandarins, almonds, walnuts, corn, and soybeans (less elastic) (Columns 1-5). Thus, the results in Table 4 suggest that the elasticity of acreage is significantly different across crops. This is consistent with the pattern of acreage changes for the tree crops, in which pistachios acreage increased by 10-fold in the last three decades.

Table 4. Acreage response regression results (Dependent Variable: Log of Harvested Acres). 2000-2019

	Corn (1)	Soybeans (2)	Almonds (3)	Mandarins (4)	Pistachios (5)	Walnuts (6)
Log of Demand shift	0.305***	0.281***	0.540***	0.611***	0.733***	0.541***
	(0.043)	(0.059)	(0.020)	(0.049)	(0.026)	(0.020)
Observations	20	20	20	20	20	20
R-squared	0.733	0.560	0.977	0.898	0.977	0.976

Notes: Dependent variable is the log of demand growth index using an average of lags for years 4, 5, and 6 for the tree crops and average lags 1 and 2 for corn and soybeans. Standard errors are in parentheses, *** p<0.01, ** p<0.05, * p<0.1.

While our main specification uses demand shift lags indicated above, in this subsection, we consider three alternative models to assess the robustness of the results in Table 4. Our first robustness test uses only *t-2* for corn and soybeans and average demand shifts in years *t-3*, *t-4*, and *t-5* for tree crops. The point estimate is 0.307 (s.e.: 0.045) for corn, and 0.281 (s.e.: 0.060) for soybeans, 0.528 (s.e.: 0.022) for almonds, 0.582 (s.e.: 0.037) for mandarins, 0.745 (s.e.: 0.031) for pistachios, and 0.515 (s.e.: 0.024) for walnuts; we cannot reject the null hypothesis that the estimate is indistinguishable from the point estimates in relevant Columns in Table 4. As a second robustness check, we estimate our modeling using a four-period lag of our demand shift measure for mandarins, five-period lag for almonds and walnuts, six years for pistachios, and one year for corn and soybeans, again; we cannot reject the null hypothesis that the estimate is indistinguishable from the point estimates in relevant Columns in Table 4.[10] Moving forward, we use Table 4 to estimate acreage elasticities (γ) for the supply elasticity calculations.

[10] Results are available up on request from the authors. We also estimated the models using average demand shifts in years t-6, t-7, and t-8 for nut crops, and cannot reject the null hypothesis that the estimate is indistinguishable from the point estimates in relevant Columns in Table 4.

1.13. Estimation of Supply Elasticities

Supply elasticities for the crops in this paper are calculated using equation (9). From equation (9), the calculation of supply elasticities requires data on acreage elasticities and elasticity of demand. Note that as acreage elasticity approaches 1, then supply elasticity becomes perfectly elastic. As acreage elasticity approaches 0, then the supply elasticity goes to 0. A more elastic demand causes the supply elasticity to increase because a given acreage shift is motivated by less of a price increase. Table 5 presents the results of the estimated demand and acreage elasticities and calculated supply elasticities by crop—the first two columns of Table 5 present acreage and demand elasticity from above. Column (3) presents the calculated supply elasticities, where pistachios have the highest supply elasticity, followed by mandarins, almonds, walnuts, corn, and soybeans.

Table 5. Calculation of Supply Elasticity from Acreage Response and Demand Elasticity (1980-2019)

Crop	Elasticity of Acreage to Demand	Demand Elasticity	Supply Elasticity
Corn	0.305	-0.35 &-0.25	0.154 & 0.110
Soybeans	0.281	-0.35	0.137
Almonds	0.540	-0.40	0.470
Mandarins	0.611	-0.50	0.785
Pistachios	0.733	-0.50	1.373
Walnuts	0.541	-0.20	0.236

It is worth noting that our estimated supply elasticities are equilibrium elasticities because they do not hold the prices of competing crops constant. That is, our acreage response equations show the net impact of acreage decisions given the historical correlations in prices, demand shifts, yields, etc. Thus, they are equilibrium acreage responses analogous to Kim and Moschini (2018) calculations of total supply elasticity. Our estimated corn and soy elasticities are lower than that of previous estimates. Still, they are broadly consistent with the most recent study on this topic, the work of Kim and Moschini (2018). They show that total supply elasticity for corn and soybeans is extremely inelastic when they accounted for the fact that corn and soybean prices are highly correlated. Kim and Moschini (2018) estimated the equilibrium supply elasticity of acreage planted to corn and soybeans together as being equal to 0.06. Our results also show quite inelastic supply responses with estimated supply elasticities of 0.11 for corn and 0.14 for soybeans.

Our findings are also in agreement with Hendricks, et al. (2014). Although the authors do not report total elasticity, their estimated own and cross-price elasticities imply that the total elasticity is even more inelastic than that of Kim and Moschini (2018). It is not surprising that our estimates are somewhat larger than the findings from the two studies mentioned, given the fact that their studies use data for only three midwestern states, IL, IN, and IA in Hendricks, et al. (2014), and 12 midwestern states in Kim and Moschini (2018). These study areas, where these two crops, i.e., corn and soybeans, account for a large proportion of annual crops planted. Therefore, their studies result in a bit more inelastic supply elasticity than our estimates. Regarding our estimated supply elasticity for nut crops, our results differ from the estimates from Russo, et al. (2008), where they estimated almonds and walnuts supply elasticity to be 0.12 and 0.02 in the short run and 12.0 and 0.08 in the long run. It is notable that our estimates of tree crop supply elasticities are more elastic than the two annual crops. The large shifts in acreage that we have observed in California for these crops support our estimates.

1.14. Consideration of Yields

Our estimates of supply elasticity do not account for possible endogeneity of yields or exogenous yield growth. We first discuss the impact if yields exogenously increase because of technological change. Our method of estimating supply elasticities calculates the change in expected equilibrium price as the difference in price with and without the demand shift after production response to a demand shift has entered the market. If yields are exogenously increasing, then the without-demand shift future price will be less than the price that would occur without higher yields. It seems reasonable to assume that growers realize the effects of increasing yields on future market prices and base their supply response to changes in demand decisions accounting for this fact. The change in future expected price that we calculate using the demand elasticity and acreage response is consistent with the assumption that growers take this lower price into account with they make their acreage decisions. Thus, relaxing the assumption of fixed yields that we implicitly made to calculate the supply elasticity has no effect on our estimates. Furthermore, when yields are exogenous, the supply elasticity equals the acreage elasticity.

If yields are endogenous, then the total production response to a demand shift will be greater than the estimated acreage response. This has two implications for our acreage elasticity estimates. The first implication is simply that the supply elasticity is the sum of the acreage elasticity and the yield elasticity, so our acreage elasticities underestimate supply elasticities if the yield elasticity is positive. The second, more subtle implication is that because the production response to a demand shift is larger than just the acreage response, then the expected price will change by less than assumed. With reference to Figure 2, the actual response will be greater than $q_1 - q_0$, which means that the anticipated price increase will be less than $p_1 - p_0$. This smaller expected price increase would make our estimated acreage elasticities somewhat more elastic because the same estimated acreage response would be motivated by a smaller expected price increase, thereby making the response more elastic. Thus, accounting for endogenous yields would increase both total supply elasticities and acreage elasticities relative to our estimates.

Discussion and Conclusion

The motivation for this research was to develop an alternative way of estimating supply and demand elasticities for use in equilibrium models of crop supply. Many such models attempt to capture grower response to changes in demand so that grower-level supply and demand elasticities are needed. However, surprisingly few estimates of grower supply elasticities are available for crops that are not traded on futures exchanges. And most demand elasticities are estimated using retail data. These consumer demand elasticities can be translated into grower demand elasticities only by making strong assumptions about the supply and demand of processing and marketing services along the supply chain between growers and consumers or by explicitly modeling the market for these services, which is a difficult undertaking for most crops.

We present an alternative method that relies on readily available public data on use, price, and acreage to estimate required elasticities. Our method also requires a substantial amount of knowledge about the crop being modeled and market information that can be used to calibrate demand shifts. While this knowledge and market information might be seen as a barrier preventing some from applying our method, it actually is no greater a barrier than that needed to correctly specify a regression model in terms of making sure that all relevant demand shifters are accounted for.

The reasonableness of the demand and supply elasticities obtained by applying our method to tree crops cannot readily be assessed because there exist so few comparable elasticities in the literature. However, the application of our method to corn and soybeans generates supply and demand elasticities that are quite consistent with recent high-quality estimates. This consistency provides some confidence that our tree crop elasticities tree crops are reasonable.

Whereas our most likely demand elasticities for almonds, mandarins, pistachios, and walnuts are all inelastic and fall in a fairly narrow range between -0.5 and -0.2, our range of estimated supply elasticities is quite wide, ranging from 0.23 for walnuts to almost 1.4 for pistachios. Notably, all our tree crop supply elasticity estimates are more elastic than the supply elasticities for our two annual crops. While this may go against the idea that supply elasticities for tree crops are more inelastic than annual crops, tree crop supply elasticity need to be quite inelastic only if inadequate time is allowed for the response to be measured by the market. Biological time lags between planting time and when bearing acreage show up in data must be accounted for when estimating tree crop elasticities.

An elastic supply response for tree crops is quite reasonable, particularly when considering the small share of total acreage that tree crops account for. Even today in California, after all the rapid growth in tree crop acreage, the largest share of acreage accounted for by the most widely planted tree crops, almonds, is much lower than the share of acreage devoted to corn and soybeans in major-producing states. Thus, one would expect a more elastic supply response.

One application of this research is an alternative to the inclusion of demand-side shifters in reduced-form price equations. Rather than focusing efforts at identifying possibly relevant demand shifters, why not simply include demand shifts directly in the regression equation? There can be no question about the appropriateness of such inclusion. After all, controls for demand shifts are used in lieu of the actual demand shifts. It seems more reasonable to just include the demand shifts directly rather than hope that the selected controls are adequate.

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