area and household density-weighted averages across census tracts comprising the relevant retailer. The first step identifies the area-weighted number of households, n_{ij}, within each Census tract i that intersects with a given retail service area j. In a second step the number of households in intersection ij was used to generate a weighted median income measure for retailer j.

In addition to median income, SDBSIM also uses retailer-specific measures of annual precipitation and summertime maximum temperature. To map weather data, points are geo-referenced at the centroid of each water agency. Based on the resulting set of points, local weather data was extracted from GIS rasters provided by the PRISM Climate Group[14]. In cases when retailer boundaries could not be mapped, a proxy zip code was used to generate the weather data for those retailers.

Model Specification

The regression equation in the SDBSIM econometric model is as follows:

$$\ln(q_{it}) = \beta_1 \cdot \ln(p_{it}) + \beta_2 \cdot \ln(p_{it}) \cdot \ln(income_i) + \beta_3 \cdot W_{it} + \mu_i + \tau_t + \varepsilon_{it} \tag{8}$$

The subscript i denotes the retailer (i = 1, … , 119), and the subscript t denotes the year (t = 1995, … , 2010). The dependent variable, $\ln(q_{it})$, is the natural log of average monthly household consumption among single-family residential households. The main right-hand side variables of interest are the natural log of price in retailer i of year t, $\ln(p_{it})$, and the natural log of price interacted with the natural log of median household income, $\ln(p_{it}) \cdot \ln(income_i)$. The sum of $\beta_1 + \beta_2 \cdot \ln(income_i)$ is the estimated price elasticity for retailer i. Notice that we obtain heterogeneity in the price elasticities by interacting $\ln(p_{it})$ with the agency-specific measure of $\ln(income_i)$. The regression equation also includes controls for weather with W_{it}, which represents annual precipitation and average summer time max daily temperature in retailer i of year t. The SDBSIM econometric model controls for unobservable factors that may bias the coefficients β_1 and β_2 by including both retailer, μ_i, and year, τ_t, fixed effects. The retailer fixed effects represent a significant advantage of this estimation specification because they control for all time-invariant unobservable characteristics that be correlated with both price and consumption. Any characteristic of a retailer that is time-invariant will be controlled for by SDBSIM.

There may still exist time-varying omitted variables at the retailer-level that bias the SDBSIM coefficients β_1 and β_2. That is, there may exist important unobserved factors that change year to year, and that are correlated with both price and consumption. For example, during a drought there may exist both conservation pricing and intensive conservation campaigns to limit water use. Although the year fixed effects in SDBSIM account for common shocks across all retailers due to drought, there is likely unobserved variation in the intensity of drought and the intensity of conservation campaigns across retail service areas—both may introduce omitted variable bias. The omitted variable, intensity of drought, would likely be positively correlated with water

[14] http://www.prism.oregonstate.edu/

consumption and negatively correlated with conservation pricing—such a correlation structure would bias the estimated price elasticities downwards. A second omitted variable, intensity of conservation campaigns, would likely be negatively correlated with water consumption and positively correlated with conservation pricing—such a correlation structure would bias the SDBSIM estimates of the price elasticities upwards. The magnitudes of these biases may be attenuated by the inclusion of the weather variables, strong predictors of drought and conservation campaigns, as retailer-level control variables in the regression. However, if there is residual variation not in these omitted variables which is not captured by weather yet is correlated with both consumption and price, then our point estimates β_1 and β_2 will be biased. SDBSIM breaks the correlation between such omitted variables and price using instrumental variables estimation. Using this estimation strategy, price is first estimated using lagged price according to the following equation:

$$\ln(p_{it}) = \alpha_1 \cdot \ln(p_{i,t-1}) + \alpha_2 \cdot \ln(p_{i,t-1}) \cdot \ln(income_i) + \alpha_3 \cdot W_{it} + \theta_i + \rho_t + \eta_{it} \tag{9}$$

Using the results of the regression in equation (2), the second step is to estimate predicted values of the natural log of p_{it}, $\widetilde{\ln(p_{it})}$, and replace the natural log of price in equation (1) with the predicted values. The final SDBSIM regression equation is[15]:

$$\ln(q_{it}) = \tilde{\beta}_1 \cdot \widetilde{\ln(p_{it})} + \tilde{\beta}_2 \cdot \widetilde{\ln(p_{it})} \cdot \ln(income_i) + \tilde{\beta}_3 \cdot W_{it} + \tilde{\mu}_i + \tilde{\tau}_t + \tilde{\varepsilon}_{it} \tag{10}$$

where the specification in equation (3) is identical to equation (1) except for the predicted values of log price.

Water Demand Estimation Results

Table 1 presents the estimation results of equation (3). Water rate variables have coefficients significantly different from zero. Importantly, there is a positive and significant coefficient on price interacted with income. This result is evidence that there is statistically significant variation in willingness-to-pay to avoid a shortage according to income levels.

15 For further explanation of Instrumental Variables estimation see Wooldridge p. 506.

Table 1 Single-Family Residential Demand Estimation Results

	Beta	S.E.	t-stat	p-value	95% C.I.	
Price	-0.415	0.079	-5.26	0	-0.570	-0.260
*Price*Income*	0.108	0.036	3.01	0.003	0.038	0.178
Precipitation	-0.012	0.009	-1.3	0.194	-0.030	0.006
Temperature	0.192	0.114	1.68	0.093	-0.032	0.415
Obs.	1186					
Year FE	Yes					
Retailer FE	Yes					
IV	Yes					

To recover the agency-specific price elasticities, SDBSIM simply takes the sum: $\beta_1 + \beta_2 \cdot \ln(income_i)$, using the agency-specific measures of median income. That is, the price elasticity of agency i equals the sum: -0.415 + .108$\cdot$ $ln(income_i)$. Table 2 shows the range of estimated price elasticities for retailers represented in the SDBSIM model.

Table 2 Estimated Retail-Level Price Elasticities

Retailer	Elasticity
Alameda Co FC & WCD Zone 7	-0.187
Alameda County W.D.	-0.197
Anaheim	-0.241
Antelope Valley East Kern	-0.208
Beverly Hills	-0.198
Burbank	-0.244
Calleguas MWD	-0.198
Castaic Lake WA	-0.198
Central Basin MWD	-0.257
City of Santa Maria	-0.268
Compton	-0.287
Eastern MWD	-0.261
Foothill MWD	-0.202
Fullerton	-0.234
Glendale	-0.251
Inland Empire Utilities Agency	-0.236
Las Virgenes MWD	-0.173
Long Beach	-0.262
Los Angeles	-0.259
MWD of Orange County	-0.210
Mojave WA	-0.261
Palmdale	-0.273
Pasadena	-0.241
San Bernardino Valley MWD	-0.322
San Diego County Water Authority	-0.240
San Fernando	-0.268
San Gorgonio Pass Water Agency	-0.282
San Marino	-0.146
Santa Ana	-0.254
Santa Clara Valley Water District	-0.189
Santa Monica	-0.231
Three Valleys MWD	-0.226
Torrance	-0.230
Upper San Gabriel Valley MWD	-0.247
West Basin MWD	-0.229
Western MWD of Riverside County	-0.241

Estimating Welfare Losses from Water Shortages

SDBSIM uses retailer-specific information on retail prices paid by customers, price elasticities of demand for various sectors, marginal costs of service delivery, and both forecasted demand and shortages for urban agencies receiving Delta water supplies[16]. The median tier price of each agency is collected to construct an agency specific price index. Price elasticities are estimated as previously described. The forecasted demand and shortages are based on the SDBSIM projections over the 83 hydrologic years.

The calculation of losses in SDBSIM is a multi-step process that starts at the level of the retailer. Losses are evaluated separately for each forecasted year for each SWP agency using its own specific economic conditions (baseline price, baseline demand, shortage level, and price elasticity). As suggested, the single-family residential sector receives the majority of shortage allocation; the exact shortage allocation rule is as follows. If an urban agency experiences a shortage in a given year then the first shortage allocation goes to the agricultural sector, which may have its supply reduced by up to 30 percent. Not all urban agencies have an agricultural supply allocation, and if they do, then it is a small sector relative to total agency water demand—as a consequence, the supply reduction in agriculture due to a shortage is small in absolute terms. Hence, the agricultural sector absorbs a relatively small share of a shortage. If there still exists a shortage after reducing the agricultural sector's supply then the next units of shortage are assigned to the single-family residential sector. The single-family residential sector is assigned up to a 30 percent supply reduction before a shortage allocation is made to the commercial and industrial sectors. The rationale for this assumption is that the single-family residential sector has more discretionary water-use, for example, outdoor water use. In a few instances, the projected shortages are so large that a full 30 percent supply reduction occurs in each of the agricultural and single-family residential sectors along with a 20 percent supply reduction in the C&I sector. In these cases, SDBSIM assigns a value of $3,000 per acre-foot to any shortage remaining.

Once an agency-level shortage in a given year has been allocated across the agricultural, single family residential and C&I sectors, SDBSIM calculates the welfare loss in each sector. For the welfare calculations the model uses the price elasticities estimated in the previous section for the single family residential sector; these range from -0.322 to -0.146. For the agricultural sector, SDBSIM employs an elasticity of -0.80, and for the C&I sector, it uses an elasticity of -0.10. These elasticities are consistent with the shortage allocation strategy in which shortage assignments are first made to the agricultural sector which has the lowest value of water, then to the single-family residential sector, and finally to the C&I sector which has the highest valuation of water.

Once the losses have been calculated they are then aggregated across agencies in SDBSIM to generate a measure of total annual losses. The total annual losses are discounted to the present using a 2.275 percent real discount rate. To account for the uncertainty of the timing of shortages this process of loss valuation is conducted for each of 83 unique hydrological trajectories.

---

16 With the exception of Kern County Water Authority.

Comments on Water Rates

The loss function in SDBSIM is dependent on baseline prices for each member agency, therefore, the definition of agency-level water rates will affect the value of water supply reliability we calculate. The index price used to characterize the water rate for households in each region is calculated from the summer rate schedule in cases where water retailers charge seasonal water rates to residential customers. For water retailers that charge volumetric rates for water, the index price used for households in the region is the volumetric price. For water retailers that implement a tiered rate structure, the relevant rate for the economic loss calculation depends on how prices are adjusted across tiers to implement a needed conservation level. SDBSIM assumes that voluntary conservation measures are adopted in proportion to household consumption levels (i.e., that all households respond to a 10 percent conservation need by cutting back water use by 10%), so that conservation is no more likely to occur among customers on any particular tier of the rate structure. The assumption of proportional adjustment of water use on all rate tiers leads to a conservative measure of index prices in the sense that conservation may be more forthcoming among households on higher pricing tiers and because agencies implementing conservation through price changes may raise water rates to a greater degree on higher rate tiers than on lower rate tiers (or alternatively reduce the quantity of water that qualifies for the lower rates), facilitating a disproportionate level of conservation on higher tiers of the rate structure than on lower tiers of the rate structure.

Under proportional rate adjustment, the relevant water rate for the economic loss calculation in equation (7) is a weighted average of the prices paid by each household in the service area for the last unit of water consumed. For many water retailers, water rates involve an inclining tiered structure, and the price index in equation (6) depends on the distribution of individual households across the pricing tiers, with the relevant rate for each household comprised of the rate paid for the last unit of water (i.e., the highest tier on which consumption takes place). That is, the price index is an index of marginal rates, which exceeds the average rate paid by households (total sales revenue divided by total water deliveries) because households on higher pricing tiers also pay lower rates on a portion of water purchased on lower tiers.

Put differently, the price index in equation (6) would accord with the average rate paid by households (total sales revenue divided by total water deliveries) for each water retailer in the case where all water units consumed by a household are priced at the rate on the highest tier of consumption. Because information is not available to construct such a price index, the index price for each water retailer is taken to be the price on the median tier of the inclining block rate structure. For most water retailers, the typical rate paid by single-family households for the last unit of consumption in summer months turns out to align with the median tier in the rate structure (frequently the second tier in a three-tiered rate structure), which is consistent with our choice of price index. The rates used in SDBSIM are net of any additional surcharges charged to customers at higher elevation zones, as cost premiums to higher elevation zones are assumed to be offset by the higher costs of pumping to these zones.

I.C. Comparing LCPSIM and SDBSIM

The SDBSIM is preferable to the LCPSIM approach as it does not just evaluate the water supply portfolio in one year of demand, but relies on demand forecasts out to 2050 in order to evaluate the water need over time. Concurrently, the SDBSIM does not only gauge the supply availability given one particular hydrologic condition at a time, as in the LCPSIM, but runs through a historical sequence of hydrologic conditions given an evolving demand. This approach captures an additional dimension of the water supply portfolio that accounts for the previous years supplies that may affect the current state through potential storage supply availability. In addition, the SDBSIM runs through 83 different possible hydrologic sequences that are matched up to forecasted water demand, creating a full picture of possible portfolio outcomes.

SDBSIM's agency level analysis, as opposed to the LCPSIM's regional level analysis, is another benefit of the model because it reveals the agency-specific value of a water shortage. This granular analysis is sought after because it more accurately assesses water supply availability throughout the model over time. The LCPSIM assumes that there are facilities and institutional agreements in place to move water as needed within a region to minimize the impact of shortage events. These assumptions are generally true for the regions assessed in the LCPSIM, however they are not appropriate for all areas and could lead to biased calculations of the benefits from additional reliability supplies. SDBSIM's agency level analysis avoids these biases, as well as makes it possible to better compute the value of agency-specific economic impacts of the resulting shortages. Since each agency within the region may have drastically different value for a unit of water, a disaggregated approach leads to a more precise representation of water value rather than valuing all agencies within a region under the same water demand estimation. Furthermore, the SDBSIM has separate loss functions for each sector within the agency while the LCPSIM uses a single residential loss function across all sectors. As a result, the SDBSIM is better able to capture the varying economic impacts across sectors.

Finally, the SDBSIM is a more desirable approach because it is a simulation model and does not endogenize water supply alternatives. The LCPSIM assumes certain levels of alternative supplies and associated costs that are integrated into the optimization of the model. This approach is problematic because it is difficult to accurately map the supply curve for alternative supplies due to the typically location-specific nature of their costs. Since LCPSIM hinges on these assumptions, the resulting welfare impact analysis will likely be biased as a result. Moreover, the implementation of new alternative supplies would most likely result in increased water prices in an attempt to recover the cost of the project. The LCPSIM does not take into account the likely decline in water demand in response to the price hike. This may also lead to biased results. Conversely, the SDBSIM treats alternative supplies as exogenous inputs. The model is flexible such that current and future alternative supplies can be selected for the model and no assumptions on costs are necessary.

II. IMPACT MODELS FOR THE AGRICULTURAL SECTOR

The Statewide Agricultural Production Model (SWAP) is an optimization model of California's agricultural economy, developed for use as a policy analysis and planning tool. The model is developed and maintained by researchers at UC Davis. It has been applied in numerous studies of California agriculture, including analyses conducted for the Bureau of Reclamation and the California Department of Water Resources.

II. A. Description of SWAP

SWAP is calibrated using the technique of Positive Mathematical Programming (PMP), which relies on observed data to deduce the marginal impacts of future policy changes on cropping patterns, water use, and economic performance (Howitt 1995). As a multi-input, multi-output model, SWAP determines the optimal crop mix, water supplies, and other farm inputs necessary to maximize profit subject to heterogenous agricultural yields, prices, and costs. SWAP's outcomes reflect the impacts of environmental constraints on land and water availability, and can be adapted to reflect any number of additional policy or technological constraints on farm production.

The PMP approach taken by SWAP allows for calibration of parameters that exactly match base-year conditions, using observed data on land use, farmer behavior, and other exogenous information. Under the fundamental assumption of profit-maximizing behavior by farmers, the model uses a non-linear objective function to derive parameters that satisfy first-order conditions for optimization under the base year's observed input and output data. While aggregate data on variables such as crop yield and acreage is often available, it is much more difficult to estimate a crop's marginal production costs. In lieu of relying on these often inaccurate estimates, the PMP technique uses the more reliable aggregate data to infer the marginal costs of production for each crop in a given region.

Aggregate data used in SWAP comes from a variety of sources. Crops are aggregated into 20 categories defined in collaboration with the California Department of Water Resources (DWR), with a proxy crop identified to represent production costs and returns for each category. Input costs and yields for the proxy crops are derived from the regional cost and return studies from the UC Extension Crop Budgets (UCCE 2011). Base applied water requirements are derived from DWR estimates (DWR 2010). Commodity prices from the model's base year are obtained from the California County Agricultural Commissioner's reports. County-level data are aggregated to a total of 37 agricultural subregions, based off of DWR Detailed Analysis Units (DAU). The SWAP regions aggregate one or more DAUs, which are chosen based on similar microclimate, water availability, and production conditions.

The SWAP model specifically accounts for both surface and groundwater supplies. In total, the SWAP model considers a number of types of surface water: State Water Project (SWP) delivery, Central Valley Project (CVP) delivery, and local deliveries or direct diversions. Where applicable, water costs include both the SWP and CVP charge as well as a district's charge. For groundwater, the model includes both the fixed costs of pumping as well as variable costs based off O&M and energy costs. For more detailed estimation of costs associated with long-run depth to groundwater changes, the SWAP model can be further linked to a separate groundwater model.

Using the input data sources described above, the SWAP model solves a PMP calibration function specified as follows for agricultural regions g, crop types i, production inputs j, and water sources w:

$$\underset{xl_{gi,land},watl_{gw}}{\text{Max}} \prod = \sum_{g}\sum_{i}(v_{gi}yld_{gi} - \sum_{j\neq water} \omega_{gij}\,\alpha_{gij})xl_{gi,land} - \sum_{g}\sum_{w}(watl_{gw}\varpi_{gw})$$

The terms $xl_{gi,land}$and $watl_{gw}$ signify land and water use. Region-specific crop prices and yield are represented by v_{gi} and yld_{gi}, while ω_{gi} and $\varpi_{gi}$are input and water costs. α_{gij} are regional Leontief coefficients, depicting the observed level of input use for each crop in each region. Farm production is constrained by the availability of land and water, which are separated in the calibration given that any individual region may be constrained by either one of the two. The land and water constraints are defined as

$$\sum_{i} xl_{gi} \leq b_{g,land} \quad \forall\, g$$

and

$$\sum_{w} watl_{gw} \leq \sum_{w} watcons_{gw} \quad \forall\, g$$

where $b_{g,land}$ and $watcons_{gw}$are land and water availability constraints in each region. The PMP approach calculates imputed "shadow values" the constraining inputs, which reflect the true value of an additional unit of land or water in the region. Each additional unit or land or water allows for additional agricultural output, which will be dependent on the crop produced and the price for that crop in the regional market. The imputed shadow values are thus a function of the revenues from constrained crops, and reveal each region's willingness-to-pay for additional units of constrained inputs as a function of their productive opportunities.

In addition to the resource shadow values for land and water, the addition of a calibration constraint forces the program to optimize according to observed base year cropping patterns. As detailed in Howitt (1995), an arbitrarily small number is included as a perturbation term (ε) to decouple the resource and calibration constraints:

$$x_{gi,land} \leq \tilde{x}_{gi,land} + \varepsilon \quad \forall\, g, i \qquad\qquad \varepsilon = 0.0001$$

The more profitable crops in the model will end up limited by the calibration constraints. The less profitable crops are not constrained by the calibration value and therefore determine the shadow values of the constrained input resources, in this case those of land and water. The shadow values on land and water are thus set equal to the marginal net return of a unit increase in those resources, which is a function of revenues from the constrained crops.

The imputed values from PMP calibration are next used to parameterize regional production functions for each crop. The production functions are specified using a constant elasticity of substitution (CES) and have constant returns to scale, as the total value of production is allocated exactly among the different inputs. The use of the CES production function allows for substitution of inputs at a specified substitution elasticities. For example, applied water rates could be partially substituted for by improving irrigation efficiency through capital expenditures on improved irrigation technology (although care should be taken to account for improvements in irrigation technology that have already occurred). The CES functions are defined as

$$y_{gi} = \tau_{gi}[\beta_{gi1}x^{\rho_i}{}_{gi11}\beta_{gi2}x^{\rho_i}{}_{gi2} + \cdots + \beta_{gij}x^{\rho_i}{}_{gij}]^{1/\rho_i}$$

Where y_{gi} represents output of crop i in region g based on the combined inputs j. The relative use of different production factors is depicted by the share parameters β_{gij}. Scale parameters are given by τ_{gi}, and x_{gij} represents production factor usage. If data is available, specific substitution elasticities can be estimated and applied. Alternatively, a fixed value for all inputs can be used. Assuming a constant elasticity of substitution σ, $\rho_i = \frac{\sigma-1}{\sigma}$.

Optimal input allocation is determined by the first order condition which sets the value of marginal product from each input equal to the marginal cash cost plus opportunity cost for that input. Using the shadow values calculated in the PMP calibration step, this value will be equal to the base input price plus the shadow values on the constrained resources. For crops bound by the calibration constraint, the calibration shadow value is additionally added. This process can be generalized for any number of regions and crops. Under the constraint of constant returns to scale, one can algebraically solve for the share values β_{gij}. Since the value of total production y is known, substituting in the calculated share values allows for final calculation of the scale parameter τ.

The next step in the SWAP model is estimation of an exponential land cost function, using information on acreage response elasticities and the calibration constraint shadow value. The use of an exponential cost function avoids problems associated with quadratic cost functions that estimate a linear marginal cost for land. Namely, linear estimates can result in negative marginal costs over a range of low land areas, forcing a modeler to adopt unrealistic marginal production costs near the lower bound in order to fit a desired supply elasticity. The use of an exponential cost function, on the other hand, bounds marginal costs above zero and thus avoids this problem. The total land cost function is defined as

$$TC_{gi} = \delta_{gi}e^{\gamma_{gi}x_{gi.,land}}$$

where δ is the minimum fixed cost of producing crop i in region g, and γ is the response function's elasticity parameter. These parameters are calculated by regressing the calibration shadow value of land against the observed base level of land use and the elasticity of supply for each crop group.

Agricultural prices in the SWAP model are treated as endogenous by calculating individual demand functions for each crop group. First, a statewide demand function for each crop is calculated using crop demand elasticities estimated by Green et al. (2008). The specified downward-sloping demand curves represent consumers' willingness to pay for each individual crop. All else equal, as production of a given crop increases its price is expected to decrease. While the statewide price is assumed to be constant across all modeled regions, regional prices are allowed to deviate due to region specific differences in production levels, crop quality, climate, and other factors.

The individual crop demand functions are specified as

$$p_i = \xi \alpha_i^1 - \alpha_i^2 \left(\sum_g \sum_j y_{gij} \right)$$

where p_i is crop price, α_i^1 and α_i^2 represent the intercept and slope of the demand curve, and ξ allows for a shift in demand due to further exogenous factors. To calculate the statewide California crop price, observed prices are weighted by the relative proportion of statewide production in each region *g*. Subtracting the statewide price from regional observed prices yields the regional marketing cost rmc_{gi}, reflecting differences in prices due to region-specific factors. At this point, the calibrated functions are aggregated into a nonlinear profit maximization program which considers farm production optimization and considers the previously specified CES production functions, crop- and region-specific exponential land cost functions, and crop demand functions specified above. Accounting for endogenous crop prices, the program maximizes the sum of producer and consumer surplus as follows:

$$\begin{aligned}
\underset{x_{gij}, wat_{gw}}{\text{Max}} \quad PS + CS = &\sum_i \left(\xi \alpha_i^1 \left(\sum_g y_{gi} \right) + \frac{1}{2} \alpha_i^2 \left(\sum_g y_{gi} \right)^2 \right) \\
&+ \sum_g \sum_i \left(rm_{gi} \left(\sum_j y_{gi} \right) \right) \\
&- \sum_g \sum_i \left(\delta_{gi} \exp(\gamma_{gi} x_{gi,land}) \right) \\
&- \sum_g \sum_i \left(\omega_{gi,supply} x_{gi,\ upply} + \omega_{gi,labor} x_{gi,labor} \right) \\
&- \sum_g \sum_i \left(\varpi_{gw} wat_{gw} \right)
\end{aligned}$$

The program optimizes for each region *g*, crop *i*, and water source *w*. The four production inputs are written out separately, as land cost is estimated by the exponential cost function, and water costs vary by source. The first term in the above equation is equal to the sum of gross revenue plus consumer surplus for each crop in each region. The second term represents region-specific additional revenue from regional crop prices higher than the statewide base price. The third term represents total land costs, the fourth represents total labor and supply costs, and the fifth and final term represents total water costs.

The authors of the SWAP model apply additional constraints to ensure the estimation of realistic outcomes (Howitt 2012). Simple input and water constraints limit model output according to the total input availability in each region. While the CES production function allows for substitution between inputs, the model is further constrained to prevent the model from reducing applied water rates below those normally observed. This ensures that applied water levels under stress irrigation are not unreasonably low.

Further constraints include limiting the amount of perennial crops which can be retired, as farmers would be expected to devote resources in the short run to preserving established perennial stands that have large investment costs. Limiting the amount of perennial retirement assumes that only older stands near retirement would be taken out of production (an assumption that may not be realistic). Additionally, a silage constraint is added to ensure that produced crops continue to meet the regional feed requirements of California dairy herds.

The model is extensible in that any number of additional constraints can be added to more accurately depict agronomic, environmental, or political conditions in an applied setting. However, some constraints may need to be relaxed in order for the model to calibrate properly. A final overall test of calibration for the model examines the difference in input allocation and production outputs between the base data and the modeled outcome, which should be nearly identical.

At this point, if the calibration test is specified the model is ready for use in policy application and sensitivity analysis. There are three fundamental assumptions that are important to note. First, the model assumes water is interchangeable among all crops in a region. Second, farmers are expected to act in a way that maximizes annual profits, by equating the marginal revenue of water to its marginal cost. Finally, it is assumed that each region adopts a crop mix that will maximize regional profits.

II.B. An Assessment of the SWAP Model

Input Data

For each crop group the modelers choose a representative crop, which reflects the variable input costs for each crop group. The table below taken from the SWAP documentation lists the crop croups and the chosen representative crop:

SWAP Crop Group	Proxy Crop	Other Crops
Almonds and Pistachios	Almonds	Pistachios
Alfalfa	Alfalfa Hay	
Corn	Grain Corn	Corn Silage
Cotton	Pima Cotton	Upland Cotton
Cucurbits	Summer Squash	Melons, Cucumbers, Pumpkins
Dry Beans	Dry Beans	Lima Beans
Fresh Tomatoes	Fresh Tomatoes	
Grain	Wheat	Oats, Sorghum, Barley
Onions and Garlic	Dry Onions	Fresh Onions, Garlic
Other Deciduous	Walnuts	Peaches, Plums, Apples
Other Field	Sudan Grass Hay	Other Silage
Other Truck	Broccoli	Carrots, Peppers, Lettuce, Other Vegetables
Pasture	Irrigated Pasture	
Potatoes	White Potatoes	
Rice	Rice	Wild Rice
Safflower	Safflower	
Sugar Beet	Sugar Beets	
Subtropical	Oranges	Lemons, Misc. Citrus, Olives
Vine	Wine Grapes	Table Grapes, Raisins

For the group grain, for example, wheat is chosen as the proxy crop for wheat, sorghum, oats and barley. The model obtains input costs of land, labor and other supplies from the University of California Cooperative Extension (2011) cost and return studies. These studies are location and crop specific detailed studies, which aid farmers in obtaining best practice estimates of input costs for a given farming technique and location for a given crop. For wheat, for example, there are two studies (2008 and 2009) which provide such estimates for irrigated wheat and wheat "for grain". The irrigated wheat study is for the Sacramento Valley and the "wheat for grain" study is for the lower San Joaquin Valley. There are no other studies available for wheat in the database the modelers cite in the model documentation.

The notes significant year to year variation in yields and extrapolates out of sample: "Reported average wheat yields in Sacramento Valley over the past ten years ranged from 1.56 to 2.58 tons per acre. [...] In this study 3.0 tons per acre is used." The 3.0 tons per acre figure is outside the range of what is actually observed in the data for this location. For irrigated wheat, the report indicates per acre operating costs of $351 per acre.

The wheat for grain study on the other hand uses yields of 3.5 tons per acre and notes a range of 2-4.5 tons per acre. The per acre operating costs are approximately $490 per ton. These are the only two data points available for wheat in all of California. These two studies are used to proxy for oats, sorghum and barley throughout California - in areas where wheat is currently grown and areas where it is not.

One could check these numbers against an available report for grain sorghum, which is available for the South San Joaquin Valley. Yields are assumed to be 4 tons per acre with a range of 2-5 tons. Total operating costs are $464 per acre. These are significant differences from the numbers for wheat which proxies for Sorghum. To illustrate the differences within group one need only look at labor requirements. The labor requirements differ quite a bit across these crops and locations. The irrigated wheat San Joaquin South study estimates 1.57 hours of labor per acre. The Sorghum study 2.17 hour and the wheat for grain study estimates 3.17 hours of labor per acre. This is 100% difference across grains within a group. The difference between sorghum and wheat in the same region is still significant (39% difference). A 39% difference in labor intensity is anything but marginal. Further the irrigation requirements by crop vary significantly The reports state that sorghum requires 30 acre inches, while wheat requires 20 acre inches, which is a 50% difference. This puts in to question the representativeness of the parameters of these costs studies as a location specific estimate for a given crop group.

Further, there is less than complete coverage for these crops across space and there is significant variation in input requirements across space as the above listed examples illustrate – even within crop group.

Water Requirement Data

While the UC Extension studies do provide estimates of water requirements for the studied crops, which resulted in the estimated yields further used by SWAP, the model does not use these, but instead uses the DWR obtained estimates, which have spatially broader coverage. The "Annual Land & Water Use Estimates" provide estimates of applied water by crop and DAU. While there is broad coverage of crops, these data are only publicly available through 2001. For any given region the number in the database for a given crop is zero as it only appears if there was observed (irrigated) area for a crop. This is problematic for a model like SWAP, which of course allows for switching into crops, which were previously not grown in a certain area. The location specific water requirements are an important determinant of this decision and appear not to be observed. For the 277 DAUs and 20 crops in 1999 there should be 5540 irrigation intensities. For 4232 out of these 5540 a zero is recorded, which indicates a missing value rate of 76%. This is of course not by intent, but rather by the fact that crops are grown in very specific areas and we do not observe most crops grown in most areas. From a practical perspective, this feature is partially offset by the fact that SWAP aggregates DAUs into SWAP regions, but the fundamental issue of missing values remains.

We have obtained only the aggregated SWAP region specific numbers for land use and applied water for 2005. Even after aggregation there remains a significant number of missing values. The issue of within region and crop group heterogeneity cannot be addressed by using these data.

Land Use Data

The land use data come from the same source as the water requirement data. Land use is aggregated to the SWAP regions for the crop groups for a single year (2005). This is clearly problematic, as one has no idea as to what the available land for crop production by crop group is. The SWAP documentation is silent on this matter. In a single year, some land will lie fallow. Further, in some years previously unused marginal lands may be converted to farmland.

Finally, not all land can produce any crop. A good example of this phenomenon is the area of Westlands Water District that is impacted by shallow groundwater. SWAP does not utilize readily available GIS layers of soil characteristics to determine the available amount of land for a given crop and the potentially available land for irrigated and non-irrigated agricultural production. There are other land use data layers available (e.g., the USDA's NASS layers) that could inform or help verify the DWR provided land use data and verify the model's fit for more than a single period.

Aggregation

SWAP aggregates production into production regions. Some of these regions follow natural boundaries such as water districts with similar water supplies (e.g., Westlands Water District). Other SWAP regions are not well defined, however. For example, SWAP Region 19 includes state and federal districts, and areas without any groundwater availability. These districts are heterogeneous enough that they should not be aggregated. Further, assuming unrestricted water trading among these districts is not realistic.

Groundwater Extraction

SWAP is not integrated with any groundwater model, and treats groundwater availability as exogenous. Thus, it does not capture the fact that if there is significant groundwater extraction the water table may fall and pumping costs may rise. In reality, groundwater extraction costs are endogenous in the long run, and will influence the shadow value of surface water.

We would add that to the extent that the SWAP does not account for variability in the quality of groundwater and its ability to serve as a suitable replacement supply for all types of crops, then the model would tend to underestimate the impacts of reductions in surface supplies. Further, it is uncertain if the model accounts for the availability of groundwater, the installed capacity to pump, and/or the ability to transport groundwater to places without availability/capacity.

Concerns about the Linear Calibration Program

In step II SWAP maximizes farmer profits and uses observed 2005 land values as the calibration constraints. The model for each region chooses land use for crop i in region g as well as water use for crop i and region g. What is known here are region specific crop prices, yields per acre for each crop and region, input and water prices as well as observed input use for all inputs except for water. The profits are maximized subject to a region specific total land constraint and source specific water consumption constraints. The model is solved using a numerical optimization routine and designed to reproduce 2005 land use patterns almost exactly.

There are a few points of concern with this approach. The model takes as given and correct the 2005 land distribution, input prices, water prices, and total land constraints. All of these values are taken as given known exactly here in order to get the all important shadow values for land

and water. If these values are observed with error, the shadow values may change radically. Howitt eloquently discusses the sensitivity of these models to changes in the input data in a recent *ARE Update* article.

Concerns about the Production Function Parameter Calibration

Step III uses Howitt's PMP approach to derive parameters for a Constant Returns to Scale Constant Elasticity of Substitution Production Function for each region and crop. While one must make some parametric assumptions in any empirical study, the choice of functional form and parameterization has significant consequences for model prediction. This is especially true in non-econometric models where the majority of parameters are not estimated based on real world data but assumed by the modeler. Below we outline the most significant assumptions made here:

- **Constant returns to scale.** The CRS assumption in most basic terms assumes that doubling all inputs exactly doubles output. In the long run a CRS production function has constant average and marginal costs of production. This has to be and should be verified by crop empirically. Whether average costs are increasing or constant has significant ramifications for optimal output choice. A decreasing returns to scale assumption is very likely a much more realistic assumption.

- **Elasticity of substitution.** SWAP assumes an elasticity of substitution between any two inputs of 0.15. This is not empirically verified and has maybe the most significant ramifications for the optimal input choice. In the most basic terms what this assumes is a very limited ability by farmers to substitute between land, labor, water and other supplies. Assuming that farmers can maintain a given output level with the same substitution flexibility between water and land as between land as between labor and other supplies is unrealistic. Further assuming that this elasticity is identical for all crops is certainly not true. They justify this assumption with "experience from previous analyses", yet given the importance of this assumption, a Monte Carlo analysis should at least be conducted to demonstrate the importance of these assumptions. It is important to note that figure 3 in the model documentation is an artificial construct and bears no connection to a specific crop or farming reality.

- **First order conditions.** The optimization program solves by setting the marginal value product equal to the marginal cash cost plus opportunity cost for the input. If there are no estimates on the marginal productivity of a crop, the modelers make the significant assumption that "marginal productivity decreases 25% over the base condition productivity and thus use 25% of the land resource shadow value". It is important again to note that this is necessary in order to make the model solve, but an assumption that will have significant consequences for the solution of the model and which is not based on farming reality but rather a somewhat arbitrary assumption on part of the modeler.

- **Numerical scaling issues.** As the model documentation notes, there are scaling issues affecting the ability of the model to arrive at a solution. The modelers provide a scaling and rescaling solution. As Knittel and his coauthors recently pointed out, these numerical solution techniques are very sensitive to starting points and solution algorithms. The model documentation does not show whether this is an issue here.

Some Additional Observations

- **Demand Functions.** The model uses linear demand functions with elasticities based on a single study (Green et al 2008). It is somewhat nonstandard to assume an elasticity at the starting point for a linear demand function as the demand elasticity is not constant along this demand function. Great care has to be paid that the model accurately reflects the demand functions estimated by Greene and their staring point relative to the 2005 number used by SWAP.
- **Drought years.** 2005 was not a drought year. It is not clear that the model can be used to represent what happens during drought years as it is parameterized based on a non-drought year. One could conduct an exercise and see how well the model predicts drought and non-drought year land use and water use.

II.C. Recommendations Regarding the SWAP Model

The SWAP model is a useful tool that has provided important insights into the impact of changes in water availability. It has a long track record of use in program evaluation, cost-benefit analysis and academic research. State and federal agency staff members are familiar with its workings, and with its results. Nonetheless, we are concerned that SWAP is built on a very large number of relatively untested assumptions. We also have concerns about the underlying data, and about the calibration procedures used to fit the model to the data. We would like to recommend that DWR undertake the following steps to improve the suite of models available to analyze agricultural impacts of changes in Delta water supplies:

- The state should conduct a systematic peer review of SWAP, focusing on the large number of assumptions underlying the model (only some of which have been described in this report).

- We recommend that the predictions of the SWAP model be tested against real-world changes in land allocation. Such a test could be undertaken via a "backcasting" exercise where SWAP is calibrated to historical conditions, ideally by an independent research team, and then used to predict the impacts of actual past changes in water availability.

- DWR should work to integrate SWAP with a groundwater model. This project takes on additional importance given the potential for large changes in water availability associated with future State Board actions.

- The UC Davis researchers should consider reconfiguring the SWAP regions to better correspond to actual water rights, project service areas, and groundwater conditions.

- DWR should develop an econometric model for the agricultural sector in the San Joaquin Valley. There is a large amount of land use data that has become available in recent years that could be used as the basis for such a model. Other models could be developed for other quantities of interest, including farm employment and its relation to water deliveries. A key advantage of an econometric model is that it would produce standard errors around forecasts, a key omission of the SWAP model.

References

DWR. California Department of Water Resources, Land and Water Use Data. Available at: http://www.water.ca.gov/landwateruse/ (Last accessed October 2012).

Green, R., et al. "Estimation of Supply and Demand Elasticities of California Commodities." Working Paper. Department of Agricultural and Resources Economics, University of California, Davis (2008).

Howitt, Richard E. "Positive Mathematical Programming." American Journal of Agricultural Economics, 77: 329-342 (1995).

Howitt, Richard E. "A Calibration Method for Agricultural Economic Production Models." Journal of Agricultural Economics, 46(2): 147-159 (1995).

Howitt, Richard E., et al. "Calibrating Disaggregate Economic Models of Agricultural Production and Water Management". Environmental Modelling & Software, 38: 244-258 (2012).

UCCE. University of California Cooperative Extension, Crop Budgets. Available at: http://coststudies.ucdavis.edu (Last accessed October 2012).

Department of Agricultural and Resource Economics
University of California, Davis

Estimation of Supply and Demand Elasticities of California Commodities

by

Carlo Russo, Richard Green, and Richard Howitt

Working Paper No. 08-001

June 2008

Giannini Foundation of Agricultural Economics

ESTIMATION OF SUPPLY AND DEMAND ELASTICITIES OF CALIFORNIA COMMODITIES

by

Carlo Russo, Richard Green, and Richard Howitt

ABSTRACT

The primary purpose of this paper is to provide updated estimates of domestic own-price, cross-price and income elasticities of demand and estimated price elasticities of supply for various California commodities. Flexible functional forms including the Box-Cox specification and the nonlinear almost ideal demand system are estimated and bootstrap standard errors obtained. Partial adjustment models are used to model the supply side. These models provide good approximations in which to obtain elasticity estimates.

The six commodities selected represent some of the highest valued crops in California. The commodities are: almonds, walnuts, alfalfa, cotton, rice, and tomatoes (fresh and processed). All of the estimated own-price demand elasticities are inelastic and, in general, the income elasticities are all less than one. On the supply side, all the short-run price elasticities are inelastic. The long-run price elasticities are all greater than their short-run counterparts. The long-run price supply elasticities for cotton, almonds, and alfalfa are elastic, i.e., greater than one.

Policy makers can use these estimates to measure the changes in welfare of consumers and producers with respect to changes in policies and economic variables.

Keywords: Consumer Economics: Empirical Analysis (D120); Agricultural Markets and Marketing (Q130); Agriculture: Aggregate Supply and Demand Analysis; Prices (Q110)

This research project was funded by the California Department of Food and Agriculture. The authors very much appreciate helpful comments on earlier revisions by Steven Shaffer and Charles Goodman.

Carlo Russo is a Ph.D. student in the Department of Agricultural Economics at University of California, Davis. He can be contacted by e-mail at russocar@primal.ucdavis.edu. Richard Green is a professor and Richard Howitt is a professor and department chair, both in agricultural and resource economics at UC Davis. They can be contacted by e-mail at green@primal.ucdavis.edu and howitt@primal.ucdavis.edu, respectively.

ESTIMATION OF SUPPLY AND DEMAND ELASTICITIES OF CALIFORNIA COMMODITIES

by

Carlo Russo, Richard Green, and Richard Howitt

June 2008

Introduction[1]

California's agricultural sector can be characterized as being in a constant state of flux. On the consumer side of the market there have many changes in recent decades. Demographically, the proportion of married women in the labor force over the past four decades has doubled. In addition, demand patterns have been influenced by health and diet concerns. For example, there has been a 350% increase in sales of organic foods during the past decade. Demands for specialized and niche products are also on the increase.

The structure of fresh vegetable sales are more concentrated with fewer and larger retail buyers, and environmental regulations are being imposed to ensure better food safety. Competition from foreign suppliers is increasing. Technological changes have occurred in the processing of agricultural materials. Morrison-Paul and MacDonald noted that food prices today often appear less responsive to farm price shocks than in the past. Their research, however, found improving quality and falling relative prices for agricultural inputs, in combination with increasing factor substitution, has counteracted these forces to encourage greater usage of agricultural inputs in food processing.

---

[1] For an excellent discussion of the changes in California's agricultural sector, see Johnson and McCalla.

On the production side, global markets and trade liberalization has greatly impacted domestic markets. Land lost to urban expansion and an ever-growing pressure on water available impact California producers. The number of farms in California is decreasing while the sizes of farms are getting larger. While the price for California's fruits, nuts and vegetables is determined in domestic and export markets, the profitability of competing field, fiber and fodder crops is influenced by federal subsidies and state regulations. These impacts on California agriculture occur as both demand and supply side policies change.

In order to better understand and evaluate the consequences of these changes on consumer and producer welfare, it is essential to obtain reliable estimates of supply and demand elasticities of California commodities. To the best of our knowledge, there is no current comprehensive study that provides accurate up-to-date supply and demand elasticity estimates of California's major crops. Frequently cited works reporting demand elasticities are Carole Nuckton's Giannini Foundation publications (1978, 1980), "Demand Relationships for California Tree Fruits, Grapes, and Nuts: A Review of Past Studies" and "Demand Relationships for Vegetables: A Review of Past Studies". However, given the significant structural changes noted above, there are many causal factors that need to be updated to generate current supply and demand elasticities.

A more recent article, "Demand for California Agricultural Commodities" by Richard Green in the winter 1999 issue of *Update* reports estimates of own-price elasticities for selected commodities. The commodities included food (in general), almonds, California iceberg lettuce, California table grapes, California prunes, dried fruits (figs, raisins, prunes), California avocados, California fresh lemons, California residential water, and meats (beef, pork, poultry, and fish). All of the elasticity estimates are reported in research publications by faculty of the Department of Agricultural and Resource Economics at the University of California at Davis. Individual sources for the commodities are given in the reference section.

The primary purpose of this research project is to obtain updated supply and demand elasticity estimates of major California commodities. That is, short and long-run own-price elasticities of supply and own price, cross-price and income elasticities of demand. In this study sophisticatedly simple models are used (Zellner). The models focus on California agriculture. As a consequence, we tried to emphasize the specificity of California supply, contrasting it when possible, with aggregate US or the most relevant competing states' supply. Modeling the demand for California commodities was a challenging task, considering that markets are integrated and often statistics about retail prices do not discriminate products by origin. Also, for most crops we focused on the demand at the wholesale level. Thus, farm gate price may be based on a standard "mark down" of the price paid by the buyers. The modeling of wholesale demand was also convenient for those products (for example nuts) that are consumed mostly as ingredients of final goods. Exceptions to this approach relate to alfalfa and tomatoes. The former commodity is a major input for the California dairy industry so we estimated a derived demand. For fresh tomatoes we estimated the consumer demand at the US level.

Each crop presented specific modeling issues which are described in detail in the following sections. A brief discussion of the theoretical foundations of the models will be given, but detailed theoretical underpinnings of the models can be found in standard microeconomic textbooks.

The analysis will start with some of the most highly valued crops in California: almonds and walnuts, alfalfa hay, cotton, rice, and fresh and processing tomatoes. Future research will examine grapes (including raisin, table, and wine); lettuce (head and leaf); citrus (grapefruit, lemons, and oranges), stone fruits (apricots, nectarines, preaches, plums, and prunes); and broccoli.

Before a discussion of the theoretical models, data sources, econometric techniques, and the empirical results a brief literature review is provided.

Literature Review

1. Some Estimated Demand and Supply Elasticites from Previous Studies

One of the first attempts to compile a table of demand elasticity estimates for California crops was Nuckton (1978). She reported own-price elasticity of demand estimates for several California commodities including apples, cherries, apricots, peaches and nectarines, pears, plums and prunes, grapes, grapefruit, lemons, oranges, almonds, walnuts, avocados, and olives. Table 1 is a compilation of the empirical estimates that Nuckton reported. Estimates for the different studies varied widely, but Table 1 attempts to summarize the results from the main studies.

In 1999 Green published more recent elasticity estimates of California commodities from various sources. The table of elasticity estimates is repeated below in Table 2.

Table 1. Selected Elasticity Estimates of California Commodities[1]

Commodity	Own-Price Elasticity of Demand	Comments
Apples	-0.458 to –0.81	Fresh; some estimates were elastic
Cherries	-4.27	Sweet; retail; based on 20 cities
Apricots	-1.345	Fresh, farm level
Peaches & Nectarines	-0.898	Fresh
Pears	elastic	Based on reciprocal price flexibilities
Plums and Prunes	-0.630	Fresh, farm level
Grapes	-0.327 (-0.267) –0.160	Fresh; table grapes (raisin) wine
Grapefruit	-1.25	Fresh, retail level
Lemons	-0.210 (-0.38)	Fresh (processing)
Oranges	-0.72 (-2.76)	Fresh farm (fresh retail)
Almonds	-1.74 (-14.164)	Domestic shelled (export shelled)
Walnuts	-0.464	Shelled; wholesale
Avocados	elastic	Based on reciprocal price flexibilities
Olives	elastic	Based on reciprocal price flexibilities

Source: Nuckton, C., "Demand Relationship for California Tree Fruits, Grapes, and Nuts: A Review of Past Studies." Giannini Foundation, August 1978.

Table 2. Estimates of Own-Price Elasticities for Selected Commodities[1]

Commodity	Own-Price Elasticity
Food (in general)	-0.42
Almonds	-0.83
California Iceberg Lettuce	-0.16
California Table Grapes	-0.28
California Prunes	-0.44
Dried Fruits (Second Stage or Conditional)	
Figs	-0.23
Raisins	-0.67
Prunes	-0.35
California Avocados	-0.86
California Fresh Lemons	-0.34
Meats(Second Stage or Conditional)	
Beef	-0.84
Pork	-0.79
Poultry	-0.58
Fish	-0.57
California Residential Water	-0.16

Source: Green, R., "Demand for California Agricultural Commodities", *Update*, Department of Agricultural and Resource Economics, Vol. 2, No. 2, Winter, 1999.

Some sources for the entries in Table 2 are as follows: food (Blanciforti, Green, and King); California iceberg lettuce (Sexton and Zhang); dried fruits (Green, Carman, and McManus); California avocados (Carman and Green); California fresh lemons (Kinney, Carman, Green, and O'Connell); and California residential water (Renwick and Green).

2. Examples of Market Conditions for Selected Commodities

A brief review of some recent selected articles illustrates the complexities of the market conditions facing California producers and consumers. In addition, a discussion of some economic factors that influence the supply and demand for certain products is given. The market situation for different crops varies dramatically. For some commodities, export and import markets are important. Other crops are perennial and have to be model differently than annual crops. Expectations of producers have to be incorporated in the supply response functions for these crops and a dynamic rather than a static approach has to be used. Rotation patterns can affect the supply response for certain crops such as alfalfa and cotton. A model for each crop has to incorporate these unique market characteristics associated with that particular crop. A few examples of the characteristic of the markets for a selected number of commodities are given below.

Alston, et al (1995) found an elasticity of demand for California almonds of –1.05. The demand for almonds in the United States is more elastic than almond demand in major importing countries. From a policy viewpoint, the inelastic demand for California almonds in export markets suggest that the industry can raise prices and profits in the short run by restricting the flow of almonds to these markets. In the long, however, this approach would lead to a decline in the almonds industry's share of the world market as competitors respond to higher prices with increased rates of almond plantings. They found little evidence for good substitutes for almonds among other nuts. Filberts in some European markets are an important exception to this rule. On the supply side, Alston et al (1995) found that almond yields in California are highly volatile, but yields can be predicted with good accuracy as a function of past yields, February rainfall, and the age distribution of almond trees. The major competitor to the California almond industry is the Spanish almond industry. Spanish almonds are a close substitute for California almonds in several European markets. This implies that changes in Spanish almond production have important effects on the California industry. Thus, a model of the almond industry must include both domestic and export markets on the demand side and the perennial nature of almond production (including alternate bearing years) on the supply side. Since there is little evidence of substitutes for almonds in the domestic market, a single-equation demand function can be estimated in order to obtain own-price and income elasticities for almonds.

With respect to table grapes, Alston et al (1997) obtained an estimated domestic own-price elasticity of demand for table grapes of –0.51, an income elasticity of demand of 0.51, and an elasticity of demand with respect to promotion of 0.16. Alston et al's (1997) study was primarily concerned with the effectiveness of promotion of table grapes. Their econometric results provided strong evidence that promotion by the California Table Grape Commission had significantly expanded the demand for California table grapes both domestically and in international markets. They evaluated the costs and benefits of a promotional campaign for various supply elasticity values. The policy implications were that the benefits from promotion were many times greater than either the total costs or the producer incidence of costs of a check-off program for table grapes. The own-price elasticity of –0.51 is inelastic implying that consumers are not very responsive to changes in prices of table grapes.

Almonds and grapes are two commodities for which international markets exist for the products. Thus, in order to properly model the supply and demand functions for these goods, exports and imports must be taken into account in addition to the domestic markets.

The own-price elasticity of demand for prunes, evaluated at the means, was found to be –0.4 by Alston et al (1998). The corresponding elasticity of demand with respect to income is 1.6, which, as they report, is larger than expected. Their study concludes that results from their analysis of the monthly, retail data support strongly the proposition that prune advertising and promotion has been an effective mechanism for increasing the demand for prunes and returns to producers of prunes. Based on their empirical results, they recommended that the prune industry could have profitably invested even more in promotion during the period of their investigation (September 1992 to July 1996).

Another perennial crop is alfalfa. Knapp and Konyar estimated the perennial crop supply response for California alfalfa. They employed a state-space model and the Kalman filter in order to generate parameter estimates as well as estimates of new plantings, removals, and existing acreage by age group. The estimated price elasticities for California alfalfa supply under quasi-rational expectations were –0.25 for the short run (one year) and –0.29 for the long run (10-20 years). The magnitudes of these supply elasticites appear reasonable with the longer-run elasticity a bit larger, as expected, in absolute value, than its short-run counterpart. In addition, Knap and Konyar found positive cross-price elasticity estimates for competing crops. Thus, producers react to prices of substitutes and act accordingly. Alfalfa is typically planted for three to four years and then removed from production. Frequently, cotton and alfalfa involve a rotation pattern. To our knowledge no one has attempted to model the rotation phenomena that exists between alfalfa and cotton. One of the models to be developed and estimated in this report incorporates this rotation pattern into the supply response models estimated for cotton and alfalfa.

ALMONDS

Figures 1A-6A in Appendix A provide a graphic overview of the domestic and foreign markets for California almonds for the years 1970-2001 (USDA). The figures contain information on marketable almond production, domestic per capita consumption, export and import of almonds, acreage in California, yield per acre, and grower price (nominal and real). A brief description of the almond industry will be given before the empirical results are presented.

Production of almonds exhibit a well-known alternate bearing-year phenomenon, that is, a high production year is followed immediately by a lower crop year and this pattern continues. Exports of almonds over the years 1970-2001 have continued to increase from less than 100 million pounds in 1970 to over 500 million pounds in 2001. Per capita consumption of almonds has also continued to increase over the same time period (Figure 2A). In 1970 per capita consumption of almonds were less than 0.4 pounds per capita and they increased to over 1 pound per capita in 2001. Acreage of almonds in California rose steadily over the years 1970-2001 from less than 200 thousand acres in 1970 to over 500 thousands acres in 2001. Per acre yield of almonds in

California exhibit a "see-saw" pattern, but the trend from 1970 has been increasing. Nominal grower prices for almonds have been volatile over the 30-year period from 1970 to 2001 reaching a peak in 1995 of $2.50 per pound. The major policy implication from Figure 6A; however, is that the real grower price, adjusted for inflation, has been steadily decreasing over the 1970-2001 period. The 2001 real grower price of almonds was barely over 50 cents per pound down from the peak real price of about $3.00 per pound in 1973. A causal glance at Figures 1A-6A in Appendix A indicates that the almond market is continually changing and a lot of world marketing forces affect California's production and sales of almonds. Supply and demand models are developed and estimated for almonds and the results are given in the next section.

Some theoretical and data issues must be addressed before the models and estimations are presented. First, should a researcher use a singe-equation approach or a system approach? In this report both approaches are presented, although single equation estimations are usually considered to be less efficient. There are several reasons for considering this model. Based on previous research work by the authors, alternative nuts were found to be weak substitutes for almonds in the United States domestic market. Similar results were also found by Alston et al (1995). Thus, the advantages of imposing theoretical restrictions such as Slutsky symmetry conditions may be of little value in a demand system or subsystem for nuts. In addition, retail prices for almonds do not exist since they are used as ingredients in confectionaries. This has two important implications. First, are the demand functions retail or farm-level demands? Wohlgenant and Haidacher developed the theoretical relationships for the retail to farm linkages for a complete food demand system. Their approach, however, assumes that both retail and farm-level prices exist. In our case retail prices do not exist so we cannot employ their approach. This limitation of the demand models needs to be considered when interpreting the elasticity estimates. For example, farm-level own-price elasticities are generally more elastic than retail own-price elasticities for food commodities. Second, this may imply that nuts are not weakly separable from other food commodities.[2] This would rule out estimating a nut demand subsystem. The model that we employed uses CPI to account for the prices of other food items and commodities.

Given the alternate bearing phenomenon of almonds, there is a demand for consumption and a demand for storage. Alston et al (1995) did not find evidence of a stockholding effect. Thus, we followed their approach and assume that the demand function reflects consumption responses and not storage effects.

Finally, there is a calendar year versus a crop year problem involved with data collection. Alston et al (1995), when they estimated the domestic demand for almonds, used total availability (harvest received by handlers) minus US calendar year net exports minus stocks carried out plus carryins as their dependent variable.

Single equation estimation: demand

Based on standard microeconomic theory, it is assumed that an individual (representative) consumer behaves in such a way so as to maximize a well defined quasiconcave utility function subject to a budget constraint (see, e.g., Deaton and Muellbauer). The domestic aggregate demand for almonds can be written as

[2] A reviewer questioned this assumption. Nuts appear to be not weakly separable from other food commodities since they are used as ingredients in other food products. One implication of weak separability is that demands for the weakly separable goods can be expressed as a function of prices within the group and group expenditure. In theory, for example, if the price of cakes decreases, then one would expect that the quantity demanded of cakes would increase and consequently the demand for nuts would increase violating one of the implications of weak separability. Weak separability of nuts could be tested in a demand system if data were available and thus, in principle, is a refutable hypothesis.

$$Q_t = f(AP_t, WP_t, CPI_t, PCIN_t) \tag{3}$$

where Q_t represents per capita almond consumption, AP_t represents the price of almonds, WP_t denotes the price of walnuts, a possible substitute for almonds, CPI_t represents the consumer price index and captures the price of all other goods, and $PCIN_t$ denotes per capita income.[3]

With respect to functional forms for the almond demand equation, Box-Cox flexible functional forms

$$\frac{Q_t^\lambda}{\lambda} = \beta_0 + \beta_1 \frac{X_{t1}^\lambda}{\lambda} + \cdots + \beta_K \frac{X_{tK}^\lambda}{\lambda} + \varepsilon_t \tag{4}$$

were estimated by maximum likelihood procedures where λ can take on any value. All of the estimations in the report are carried out using SHAZAM, version 10. The linear and double logarithmic forms are special cases of the Box-Cox specification. The linear and double-log functional forms in the almond demand equation were tested against the more flexible Box-Cox functional form and in both cases the linear and double-log specifications were strongly rejected. The values of the likelihood ratio statistics were 43.7 for the linear and 14.85 for double-log model. The chi-squared critical value with one degree of freedom is 3.841 at the five percent significance level. Table 1 presents the estimations. The homogeneity condition of degree zero in all prices and income (HOD) does not hold globally in the Box-Cox specification unless the functional form is double

[3] Demand theory describes the behavior of individual consumers. The estimations, however, use aggregate data over all consumers. This can result in aggregation biases. If the observations are time series of cross-section data on randomly selected households, then it can be shown that the aggregate coefficients converge, as the number of households (N) goes to infinity, in probability to the micro coefficients (Theil). The disturbance terms are heteroskedastic, however. White's heteroskedastic-consistent standard errors for the estimated coefficients must be used. A recent excellent and thorough treatment of the conditions needed to avoid aggregation bias including exact aggregation and the distributional approach is given in Blundell and Stoker. They consider heterogeneity of consumers and distribution of income over time.

log.[4] The linear, double-log, and Box-Cox estimated functional forms for almond demand equations are presented in Table 3. In order to make the different models comparable, homogeneity was imposed in the double-log models and the other models were deflated by CPI.

[4] The homogeneity condition is $\lambda = 0$ *and* $\Sigma\beta_j = 0$ where the $\beta's$ are price and income coefficients; see Pope, *et al*. Linear specifications cannot be HOD by construction.

Table 3. Almond Demand Functions[1]

	Linear	D. Log	D. Log-A[2]	Box-Cox	Box-Cox-A[3]
AP[4]	-0.0016	-0.480	-0.377	-0.2671	-2.386
p-value	(0.0036)	(0.0004)	(0.0010)	(0.0004)	(0.0007)
elasticity	-0.351	-0.480	-0.377	-0.477	-0.378
WP[5]	0.0001	0.103	0.002	0.0436	-0.0267
p-value	(0.3898)	(0.5895)	(0.9912)	(0.5948)	(0.9891)
elasticity	0.465	0.103	0.002	0.097	-0.002
PCIN	0.00001	0.870	0.973	0.2911	29.404
p-value	(0.000)	(0.0038)	(0.0120)	(0.0036)	(0.0251)
elasticity	0.465	0.870	0.973	0.864	0.928
Const	-0.403	-5.14	-5.429	-4.270	-78.211
p-value	(0.000)	(0.0042)	(0.0068)	(0.0319)	(0.0394)
R^2	0.62	0.74	0.80	0.74	0.82
lnL	28.484	14.051	17.66	35.91	40.239
λ				0.107	-0.340
ρ			0.49		0.56

[1] *Q* is in pounds per capita, *AP* and *WP* are in cents per pound, and *PCIN* is in dollars.
[2,3] "A" denotes autocorrelated correction models.
[4,5] These are grower prices since retail prices do not exist.

The models were estimated using annual data from 1970 to 2001, a total of 32 observations. The Durbin-Watson values were 1.23 and 1.12 in the linear and double-log functional forms. The critical values are 1.244 and 1.650 at the five percent significance level, thus in the double-log and Box-Cox specifications the models were also estimated with an AR(1) error process. The estimated autocorrelation coefficients were 0.49 (double-log) and 0.56 (Box-Cox) with an estimated asymptotic standard error of 0.15 (double-log) and 0.14 (Box-Cox). The estimated own-price elasticity of domestic demand for almonds ranged from –0.48 to -0.35. The estimated elasticity was -0.38 in the Box-Cox functional form with an AR(1) error process. The estimates were highly significant with small p-values. Also, the estimated cross-price elasticity with walnuts was positive in four of the five models, but none of the coefficients were statistically significant; the smallest p-value being 0.39. The results confirm the absence of gross substitution effects between almond and walnuts. All of the estimated income coefficients were positive and ranged from 0.46 to 0.97 with small p-values. A sequential Chow and Goldfeld-Quandt test was conducted to determine if any structural changes had taken place during this period. No evidence was found of any structural changes.

Additional models were estimated using the dependent variable, US total consumption of almonds plus California exports minus US imports. The dependent variable captures the international demand for US almonds as well as the domestic demand. The ordinary least squares estimated double-log regression had an R^2 of 0.92. The estimated own-price elasticity of demand for almonds was -0.270 with an associated p-value of 0.022. The estimated model had a positive time trend coefficient of 0.05 (p-value =0.03) income elasticity was 2.10 with a p-value of 0.07.

Single equation estimation: supply

On the supply side, estimated almond acreage, yield, and marketable production functions were estimated for the period 1970 to 2001. The almond acreage was estimated using a partial adjustment model of the form:

$$\begin{aligned} A_t^* &= \alpha + \beta P_t \\ A_t - A_{t-1} &= (1-\gamma)\left(A_t^* - A_{t-1}\right) + \varepsilon_t \end{aligned} \tag{5}$$

where equations (5) are the desired almond acreage and equation (6) is the actual acreage; respectively. By substitution and some simplifications, the model can be estimated as:

$$A_t = (1-\gamma)\alpha + (1-\gamma)\beta P_t + \gamma A_{t-1} + \varepsilon_t \tag{6}$$

where A_t is the almond acreage (in acres), P_t is the average real almond grower price per pound over the previous eight years and, and ε_t is an error term included to capture all omitted factors that affect almond acreage.

This specification was chosen because it incorporates the behavior of producers whom adjust their acreage when they realize that the desired acreage (A_t^*) differs from the actual acreage the previous year (A_{t-1}). The adjustment coefficient, $1-\gamma$, indicates the rate of adjustment of actual acreage to desired acreage. The partial adjustment model is a model that captures producers' behavior (see, e.g., Kmenta). Almond trees take between five and six years to be fully productive. The acreage equation assumes a long-run planning process based on past prices, which are considered a proxy of the farmers' expectations about future prices.

The estimated acreage equation, with all variables expressed in logarithm form and based on 1979-2001 annual observations, is:

$$\underset{}{\ln \hat{A}_t = -0.32 + 0.12 \ln P_t + 0.97 \ln A_{t-1}} \quad (7)$$
$$(0.31)\ (0.03) \qquad (0.04)$$

The values in parentheses are standard errors. The coefficient of determination of the regression is R^2=0.97. The Durbin-h statistic is 1.40 which is asymptotically not significant, thus there is no evidence of autocorrelation. The estimated short-run price elasticity is 0.12 with an associated p-value of 0.0016. The estimated coefficient on lagged acreage is 0.97 with an associated p-value of 0.0000. The estimated acreage response equation provides empirical evidence that almond producers respond positively to anticipated price increases in almonds.

The yield equation for almonds is:

$$\ln Y_t = \beta_1 + \beta_2 \ln P_{t-1} + \beta_3 Rain_t + \beta_4 T_t + \beta_5 T_t^2 + \varepsilon_t \quad (8)$$

where Y_t is almond yield in pounds per acre, P_{t-1} is the real grower price of almonds in cents per pound in the previous year, $Rain_t$ is rainfall in inches in March, and T_t is a time trend that is a proxy for technological change.

The ordinary least squares estimated yield equation for almonds for the years 1971-2001 is (equation (9))

$$\ln \hat{Y}_t = 6.39 + 0.07 \ln P_{t-1} - 0.20 \ln Rain_t + 0.05 T_t - 0.001 T_t^2 \quad (9)$$
$$(0.48)\ (0.09) \qquad (0.05) \qquad (0.01) \quad (0.0003)$$

where the values in parentheses are standard errors. The estimated R^2 is 0.68 which indicates an adequate fit of the model with the data. All of the p-values for the estimated coefficients are less than 0.10 except for one associated with lagged price. The coefficient on lagged price is positive (0.07) but not significant. The coefficient on

March rainfall is negative (-0.20) reflecting the effect of rain on increased brown rot disease and decreased pollination. The coefficient on the time trend is positive (0.05) and significant indicating that, conditioned on all the other variables, yields are increasing over the time period, 1971-2001. The coefficient on time squared is negative (-0.001) and significant reflecting that the time trend is increasing at a decreasing rate. The increasing trend can be due to technology and improvement of production practices. The almond yield equation exhibits an alternate bearing phenomenon since the autocorrelation was negative ($\hat{\rho} = 0.38$) with an asymptotic t-value of 2.26.[5] The model was estimated using the autocorrelation method of Pagan in SHAZAM. The other autocorrelation methods, ML and Cochrane–Orcutt gave similar results.

Finally, a production function for almonds was developed and estimated. The model is:

$$\ln Q_t = \beta_1 + \beta_2 \ln P_{t-1} + \beta_3 \ln Rain_t + \beta_4 \ln Q_{t-1} + \varepsilon_t \tag{10}$$

where Q_t is California almond production in millions of pounds, P_{t-1} represents the lagged price of almonds in cents per pound, $Rain_t$ represents March rainfall in inches, and Q_{t-1} denotes lagged production. The model is a partial adjustment model and includes the effect of alternate crop years and weather. As in the yield equation, the alternative bearing phenomenon is captured by a negative autocorrelation coefficient.

The estimation of the model, correcting for autocorrelation, is

---

[5] Several methods were used to capture the alternate-year yield phenomenon. For example, a dummy variable was added to the function with zero values for low-yield years and ones for high-yield years. Due to weather conditions and new varieties of trees that started bearing, the data exhibits a high-low pattern for a number of years followed by two high-yield years in a row or two low-yield years in a row. The high-low pattern continues for a few years but the pattern may be reversed. History then repeats itself. It is difficult to capture these phenomena with a dummy variable in the systematic part of the equation. This

$$\ln \hat{Q}_t = -0.44 + 0.19 \ln P_{t-1} - 0.20 \ln Rain_t + 0.97 \ln Q_{t-1} \qquad (11)$$
$$(1.24)(0.15) \qquad (0.07) \qquad (0.11)$$

where the numbers in parentheses are estimated standard errors. The R^2 of the model is 0.71. The elasticity of production with respect to the lagged own price (for given values of the production in the previous year, the weather conditions and the alternate crop years) is 0.19 but not significant (p-value= 0.20). The coefficient on March rainfall is negative as explained above and the estimated coefficient on lagged production is positive and highly significant. The alternate crop pattern was capture by a negative autocorrelation coefficient of -0.55 with an associated asymptotic t-value of 3.74.[6]

WALNUTS

Data for the years 1970-2001 are presented in Appendix B for walnuts. California marketable production, total domestic consumption, exports and imports, per capita consumption, acreage, yield, and grower prices, both nominal and real for walnuts are given in Figures 1B-6B in Appendix B. An overview of the walnut industry can be seen by an examination of the Figures. Marketable production of walnuts has slowly increased from just below 100 million pounds in 1970 to over 250 million pounds in 2001. Exports of walnuts exhibit a similar pattern of that to production (see Figure 1B in Appendix B). Per capita consumption of walnuts has remained relatively stable at 0.4 pounds over the period 1970-2001 (Figure 2B). Acreage has slowly increased over the period starting with about 150 thousand acres in 1970 to about 200 thousand in 2001.

---

was not the case with walnuts where the alternate pattern was consistent throughout the sample period. See the patterns in the data for almond yields, walnut yields, and walnut production in Appendix C.

[6] Alternative functional forms of the production function were estimated including a Box-Cox specification, models with moving average error schemes, etc. The Box-Cox functional form yielded a price elasticity of 0.29 and a model estimated with a moving average error term yielded a slightly lower price elasticity estimate of 0.23.

Yields of walnuts are more volatile over the period than acreage but with a steady trend upward over the period 1970-2001 (Figure 4B). Real grower prices have decreased over the period from 1970 to 2001 (Figure 6B). Real grower prices reached a peak in about 1978 of $2.00 per pound and have declined ever since to about 60 cents per pound in 2001.

Demand, acreage, yield, and production equations were estimated for walnuts using annual data from 1970 to 2001. The United States domestic demand for walnuts is estimated and reported first.

The model for US per capita consumption of walnuts is

$$Q_t = f(AP_t, WP_t, CPI_t, PCIN_t) \tag{13}$$

where Q_t represents per capita walnut consumption in pounds, AP_t represents the price of almonds in cents per pound where almonds are a possible substitute for walnuts, WP_t denotes the price of walnuts in cents per pound, CPI_t represents the consumer price index and captures the price of all other goods, and $PCIN_t$ denotes per capita income in dollars.

The restriction of homogeneity of degree zero in all prices and income was imposed. When the model for all the years, 1970 to 2001, was estimated by ordinary least squares, the Durbin-Watson value was small (0.796) indicating a possible misspecified model. Consequently, sequential Chow and Goldfeld-Quandt tests were performed and they indicated a structural break in 1983. Two demand functions were estimated, one using data from 1971 to 1983 and one employing data from 1983 to 2001. The estimated models, double-log and Box-Cox functional forms, are presented in Table 4.

Table 4. Walnut Demand Functions

	Pre 1983		Post 1983	
	Double Log	**Box-Cox**	**Double Log**	**Box-Cox**
AP	-0.210	-0.449	-0.082	-0.19E-06
p-value	(0.039)	(0.136)	(0.325)	(0.667)
elasticity	-0.210	-0.197	-0.082	-0.023
WP	-0.284	-0.825	-0.267	-0.26E-07
p-value	(0.068)	(0.113)	(0.063)	(0.051)
elasticity	-0.284	-0.266	-0.267	-0.251
CPI	-1.039	-1.435	-0.633	-0.61E-05
p-value	(0.029)	(0.612)	(0.414)	(0.307)
elasticity	-1.039	-0.677)	-0.633	-0.807
PCIN	1.534	5.349	-0.983	0.10E-09
p-value	(0.007)	(0.339)	(0.201)	(0.398)
elasticity	1.039	1.207	-0.983	0.427
Constant	-7.361	-17.519	-4.50	-0.333
p-value	(0.005)	(0.304)	(0.207)	(0.000)
R^2	0.759	0.763	0.705	0.726
DW	2.563	2,43	2.069	2.507
lnL	15.988	26.029	25.492	44.217
λ	0	-0.15	0	2.06

The R^2 values range from 0.71 to 0.76. The fit of the models to the data was not as good as for the almond demand equations. The Durbin-Watson statistics did not indicate any problems with autocorrelation. The estimated own-price elasticity of demand for walnuts ranged from –0.266 to -0.284 for the time period prior to 1983 and from -0.251 to -0.267 after the year 1983. The p-values were 0.068 (pre 1983) and 0.63 (post 1983) for the double-log models and 0.113 (pre 1983) to 0.051 (post 1983) for the Box-Cox functional forms. The Box-Cox equation post 1983 was estimated with a time trend. Its estimated coefficient was -0.03 with an associated p-value of 0.014. Three of the four estimated income elasticities were positive with only the post 1983 for the double-log specification negative (-0.983). Only one of the estimated almond cross-price elasticities was significant at any reasonable level. Thus, the sample evidence finds little substitution effects between almonds and walnuts. Based on the sample evidence the estimated own-price elasticity of demand for walnuts is inelastic.

What are some economic factors that can explain the structural break around 1982-83? From Figure 6B, real walnut prices dropped dramatically in 1983. There was a large supply of walnuts that year and inventory levels increased significantly. In addition, the United States imposed a tariff on pasta and Italy, one of the largest importers of U.S. walnuts, retaliated by placing an embargo on U.S. walnuts. Exports dropped causing increases in inventory levels.

Another model was estimated where the dependent variable was US total consumption of walnuts plus California exports minus US imports. The dependent variable captures domestic plus net export demand. Again, sequential structural tests indicated a structural break around 1983. The results from this estimated equation yielded a total own-price elasticity of demand for walnuts of –0.354 prior to 1983 and an estimated value of –0.061 after 1983. The estimated coefficient of determination for this equation was 0.923. The wide difference between the estimated own-price elasticities of demand between the two time periods may be due, in part, to structural changes mentioned above. The primary policy implications are that the demand for walnuts is inelastic with little evidence that almonds are an important substitute for walnuts.

On the supply side, acreage, yield, and production equations were estimated for walnuts, using a partial adjustment model. The estimated acreage equation is

$$\begin{aligned} \ln \hat{A}_t = {} & 2.90 + 0.02 \ln P_t + 0.00T_t + 0.00T_t^2 + 0.74 \ln A_{t-1} \\ & (1.16) \quad (0.01) \qquad (0.00) \quad (0.00) \quad (0.10) \end{aligned} \tag{14}$$

where A_t represents acreage of walnuts in acres, P denotes walnuts grower prices of walnuts in cents per pound and T is a time trend. Values in parentheses represent standard errors. The estimated coefficient of determination, R^2, was 0.953. The estimated short-run elasticity of acreage with respect to price is 0.02, which implies that acreage is inelastic with respect to the current price. The estimated lagged acreage coefficient was 0.74 and highly significant indicating a partial adjustment by producers of walnut acreage over time. Figure 6 charts the actual acreage of walnuts to the predicted values.

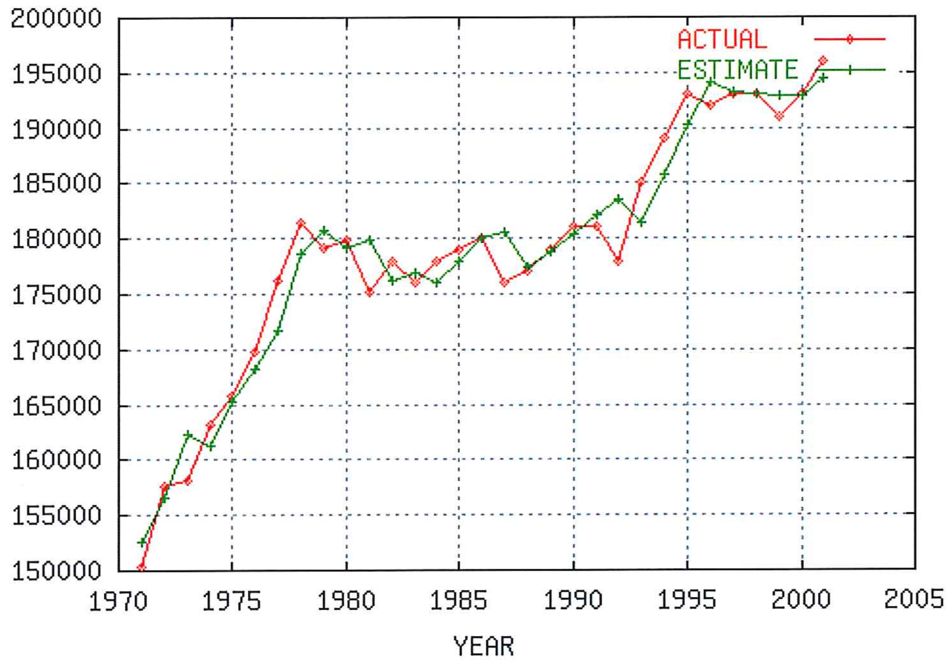

Figure 1: Walnuts acreage. Actual and estimated (in acres).

The value of the Durbin h statistic (-0.37) indicates that autocorrelation is not a problem.

The ordinary least squares estimated yield equation for walnuts, based on the years 1972-2001, is

$$\begin{aligned}\ln \hat{Y}_t = &-0.01 - 0.03 \ln P_{t-1} + 0.03 TAM_t + 0.14 D_t + 0.01 T_t - 0.0002 T_t^2 \\ &(0.60)\ (0.08) \qquad (0.03) \qquad (0.03) \quad (0.01) \quad (0.0003)\end{aligned} \qquad (15)$$

where Y_t, the dependent variable is yield of walnuts in pounds per acre, P_{t-1} is lagged real grower price of walnuts in cents per pound, T_t is a time trend, TAM_t is the average temperature in March, D_t is a dummy variable that is equal to one in high-yield years and zero for low-yield years (more specifically, D=1 in 1970 and alternates from 1 to 0 throughout the sampling period) and is included to capture the alternate yield-year phenomenon. The coefficient of determination is 0.72. The Durbin-Watson calculated value of 1.78 does not support evidence of negative correlation. The "see-saw" pattern exhibited by walnut yields is more consistent that than for almond yields and thus the dummy variable included in the systematic part of the equation picks up the alternative bearing phenomenon (see Appendix C). The estimated coefficient on D is positive and highly significant as expected and the coefficient on March temperature is positive as expected but not significant. There is a little evidence of a positive time trend. The lagged price coefficient is unexpectedly negative but not significant.

The final estimation for walnuts consists of estimating a production function for the years 1971-2001. The estimated production function, corrected for autocorrelation, is:

$$\ln P\hat{R}_t = \underset{(1.84)}{3.52} + \underset{(0.06)}{0.003} \ln P_{t-1} + \underset{(0.02)}{0.03} TAM_t + \underset{(0.07)}{0.23} D_t + \underset{(0.13)}{0.69} \ln PR_{t-1} \tag{16}$$

where the dependent variable, PR_t, is walnut production in millions of pounds, P_{t-1} is walnut price in cents per pound, TAM_t is the March temperature, and D_t is a dummy variable that takes on the values of 1 and 0 and accounts for the alternate year production phenomenon. The R^2 of the regression is 0.82. The estimated autocorrelation coefficient is -0.47 with as asymptotic t-value of 2.60. The alternate year dummy coefficient is positive and highly significant as expected is picking up all the alternate production year effect. The estimated coefficient on lagged walnut price is positive but insignificant and the estimated coefficient on lagged production is positive and significant. The positive sign on March temperature is as expected.

SUR Estimation

The results of the estimations suggest that walnuts and almonds cannot be considered as close substitutes or complements because the cross-price elasticities were not significantly different from zero. However, the possible relations across the two markets can be explored using a demand system of *seemingly unrelated equations* (SUR). In this system, correlation in the errors across equations is assumed. Some of the same omitted factors may influence both almond and walnut demands.

The equations are estimated using an iterative SUR procedure to achieve efficiency. Also the properties of symmetry and zero homogeneity were imposed. The estimation of the system (eq. 17) is:

$$\begin{aligned}
\ln PC_t^W &= -4.17 - 0.14 \ln P_t^W - 0.20 \ln P_t^A - 0.48 \ln CPI_t + 0.82 \ln PCIN_t - 0.19 T_t - 0.07 D_t \\
&\quad\ (3.57)\quad (0.14) \qquad\quad (0.08) \qquad\quad (0.07) \qquad\quad (0.78) \qquad\qquad (0.01) \quad (0.08) \\
\ln PC_t^A &= -5.45 - 0.20 \ln P_t^A - 0.18 \ln P_t^W - 0.67 \ln CPI_t + 1.05 \ln PCIN_t \\
&\quad\ (1.64)\quad (0.08) \qquad\quad (0.17) \qquad\quad (0.40) \qquad\quad (0.29)
\end{aligned}$$

where numbers in parentheses are standard errors, PC^W and PC^A are the per-capita consumption of walnuts and almond, respectively. PC^W and PC^A are grower nominal prices of walnuts and almonds, respectively, D_t is a dummy variable that takes on the value of zero prior to 1983 and the value of one after 1983. The remaining variables are as defined above except per capita income is also expressed in nominal terms. The system R^2 is equal to 0.81. The estimated own-price elasticity of walnuts is -0.14 and that of almonds -0.20; with only the estimated own-price elasticity of almonds being highly significant. The estimated income elasticity for walnuts is 0.82 and that of almonds is 1.05.

Some Policy Implications

Based on the models estimated for almonds and walnuts the own-price elasticity of US domestic demand for almonds was found to be between –0.35 and -0.48.. These estimates are inelastic and imply that almond producers are vulnerable to large swings in prices of almonds due to supply shifts. Similar estimates of the own-price elasticity of US domestic demand for walnuts were obtained. The estimated own-price elasticities for walnuts ranged from –0.25 to –0.28. Walnut producers face the same marketing situation as almond producers, that is, prices of walnuts fluctuate widely due to shifts in the supply function of walnuts.

The estimated acreage response equation for almonds indicated that producers respond positively to lag prices. The estimated short-run price elasticity of acreage for almonds was 0.12 and significant. This is relatively small but does indicate that producers are responsive to increases in prices over time. For walnuts the estimated short-run price elasticity of acreage was 0.02 and significant. Again, the value is small but positive.

The estimated yield equations for both almonds and walnuts reflected a significant alternate-year phenomenon. For almonds the phenomenon was capture by a significant and negative autocorrelation coefficient. For walnuts it was captured by a dummy variable. Yields for almonds are significantly affected by a time trend. Yields of almonds are increasing over the time period 1979-2001, based on the estimated yield equation. For walnuts, yields were positively affected by temperature in March and a time trend, but neither coefficient was significant.

A SUR demand system was estimated for walnuts and almonds. The domestic own-price elasticity of demand for walnuts was estimated to -0.14 and that of almonds -0.20 with almonds being significant. The estimated income elasticity of demand for walnuts was 0.82 and that for almonds was 1.05 with the estimated income elasticity in the almond equation being significant. The evidence does not support gross substitution between almonds and walnuts.

The primary policy implication based on these results is that almond and walnut producers are facing an inelastic domestic demand for their products. Combine this with the volatility of the supply function due to temperature and rainfall changes, wide variations in prices exist which lead to wide variations in profits from year to year. Storage, improved technology, and an expanding export market are factors that may mitigate the volatile market conditions facing US producers of almonds and walnuts.

References

Alston, J., H. Carman, J. Christian, J. Dorfman, J-R. Murua, and R. Sexton, "Optimal Reserve and Export Policies for the California Almond Industry: Theory, Econometrics and Simulations." *Giannini Foundation Monograph*, No. 42, February 1995.

Alston, J., J. Chalfant, J. Christian, E. Meng, and N. Piggott, "The California Table Grape Commission's Promotion Program: An Evaluation." *Giannini Foundation Monograph*, No. 43, November 1997.

Alston, J., H. Carman, J. Chalfant, J. Crespi, R. Sexton, and R. Venner, "The California Prune Board's Promotion Program: An Evaluation." *Giannini Foundation Research Report*, No. 344, March 1998.

Blanciforti, L., R. Green, and G. King, "U.S. Consumer Behavior Over the Postwar Period: An Almost Ideal Demand System Analysis." *Giannini Foundation Monograph*, No. 40, August 1986.

Blundell, R. and T. Stoker, "Heterogeneity and Aggregation", *Journal of Economic Literature*, 43(June 2005):347-391.

Carman, H. and R. Green, "Commodity Supply Response to a Producer Financed Advertising Program: The California Avocado Industry" *Agribusiness: An International Journal*, 1993, 605-621.

Goodwin, B. and G. Brester, "Structural Change in Factor Demand Relationships in the U.S. Food and Kindred Products Industry.' *American Journal of Agricultural Economics 77(1995):69-79.*

Green, R., H. Carman, and K. McManus, "Some Empirical Methods of Estimating Advertising Effects in Demand Systems: An Application to Dried Fruits." *Western Journal of Agricultural Economics 16(1):63-71.*

Green, R., "Demand for California Agricultural Commodities." *Update* Vol. 2, No. 2, Winter 1999.

Johnston, W. and A. McCalla. "Whither California Agriculture: UP, Down, or Out? Some Thoughts about the Future." *Giannini Foundation Special Report* 04-1, August 2004.

Kinney, W., H. Carman, R. Green, and J. O'Connell, "An Analysis of Economic Adjustments in the California-Arizona Lemon Industry." *Giannini Foundation Research Report,* No. 337, April 1987.

Kmenta, J. *Elements of Econometrics*, 2nd ed., Macmillan Pub. Co., New York, 1986.

Knapp, K. and K. Konyar, "Perennial Crop Supply Response: A Kalman Filter Approach." *American Journal of Agricultural Economics*, 73(1991):841-849.

Morrison Paul, C. and J. MacDonald, "Tracing the Effects of Agricultural Commodity Prices and Food Costs." *American Journal of Agricultural Economics* 85(2003):633-646.

Nuckton, C., "Demand Relationships for California Tree Fruits, Grapes, and Nuts: A Review of Past Studies", *Giannini Foundation Special Publication* No. 3247, August 1978.

Nuckton, C., "Demand Relationships for Vegetables: A Review of Past Studies", *Giannini Foundation Special Report 80-1*, 1980.

Pope, R., R. Green, and J. Eales, "Testing for Homogeneity and Habit Formation in a Flexible Demand Specification of U.S. Meat consumption" *American Journal of Agricultural Economics* 62(1980): 778-784.

Renwick, M. and R. Green, "Do Residential Water Demand Side Management Policies Measure Up? An Analysis of Eight California Water Agencies" *Journal of Environmental Economics and Management* 40(2000):37-55.

Sexton, R. and M. Zhang, "A Model of Price Determination for Fresh Produce with Application to California Iceberg Lettuce." *American Journal of Agricultural Economics* 78(1996):924-34.

Wohlgenant, M. and R. Haidacher, "Retail to Farm Linkage for a Complete Demand System of Food Commodities", USDA, ERS, Technical Bulletin No. 1775, 1989.

Zellner, A. "Philosophy and Objectives of Econometrics", *Journal of Econometrics*, 2006.

Appendix A: Almonds

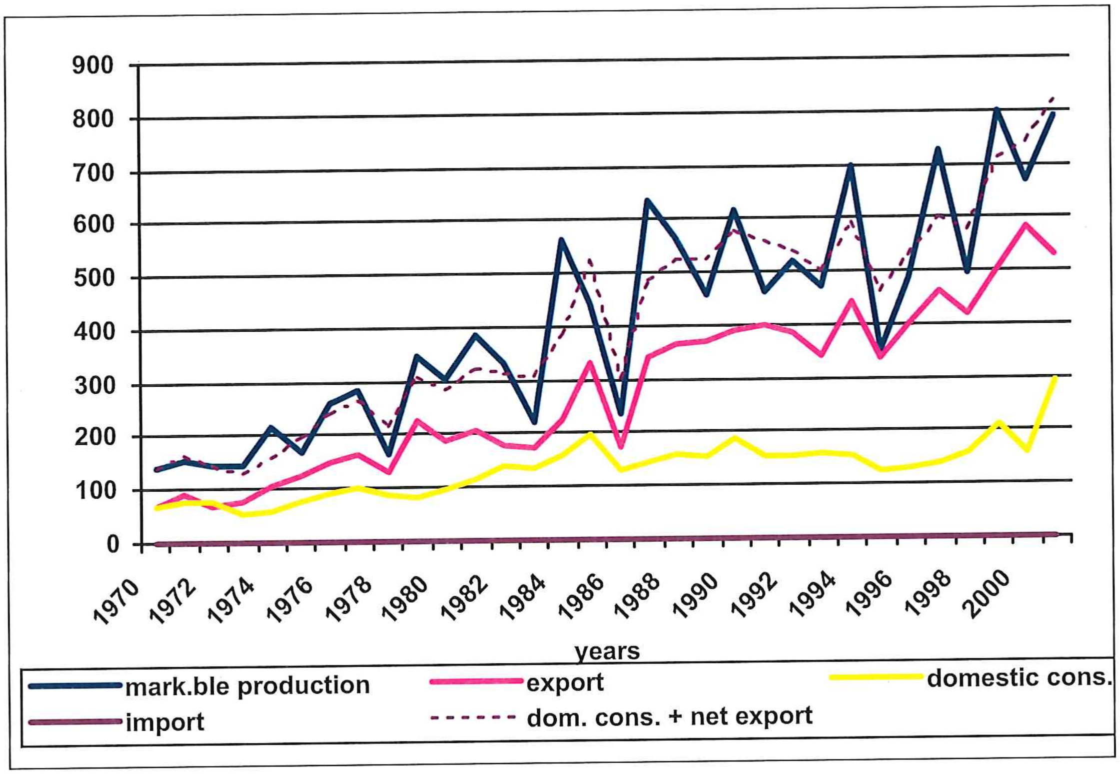

Figure 1A: California marketable production, US domestic consumption, export and import of Almonds. Years 1970-2001(millions of lbs).

Source: USDA

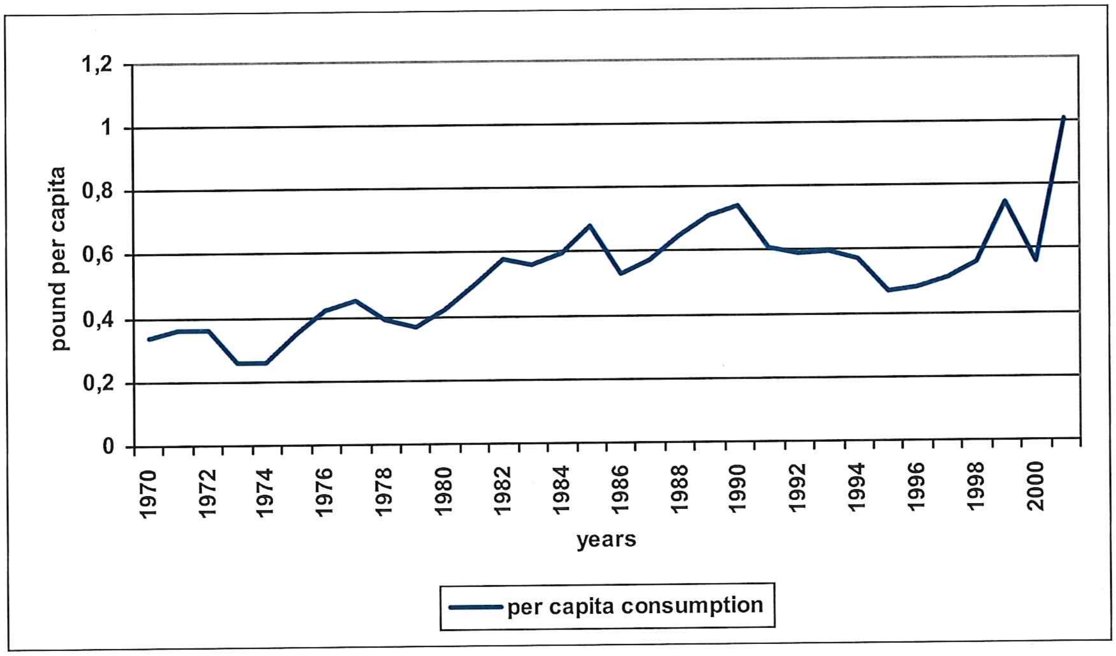

Figure 2A: US per capita consumption of Almonds. Years 1970-2001

Source: USDA

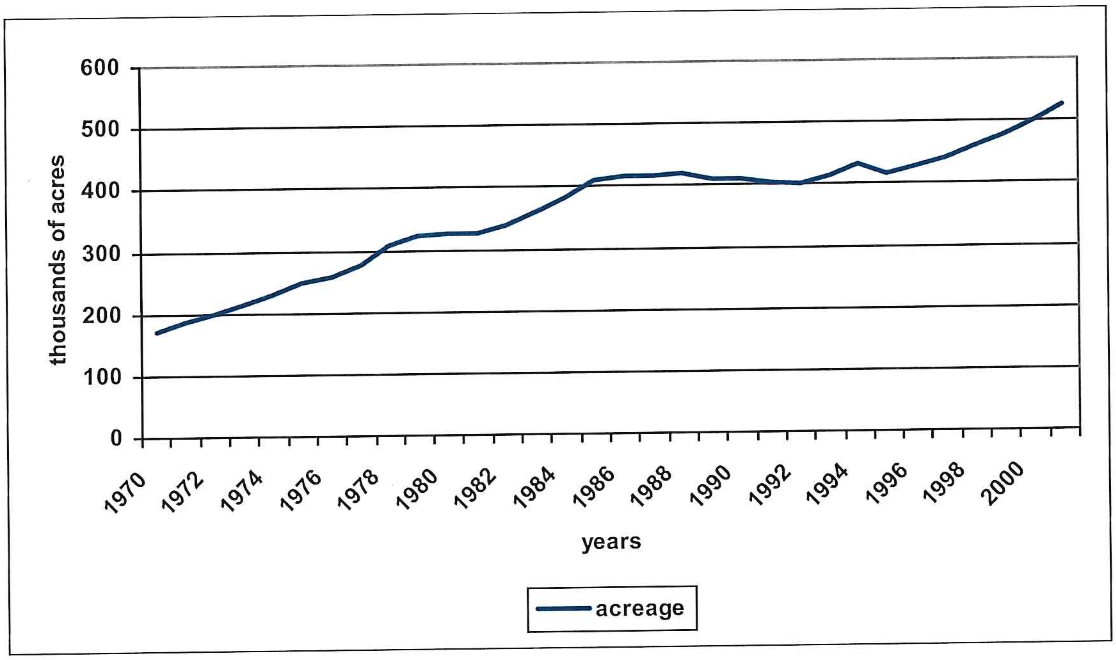

Figure 3A: Acreage of almonds in California. Years 1970-2001

Source: USDA

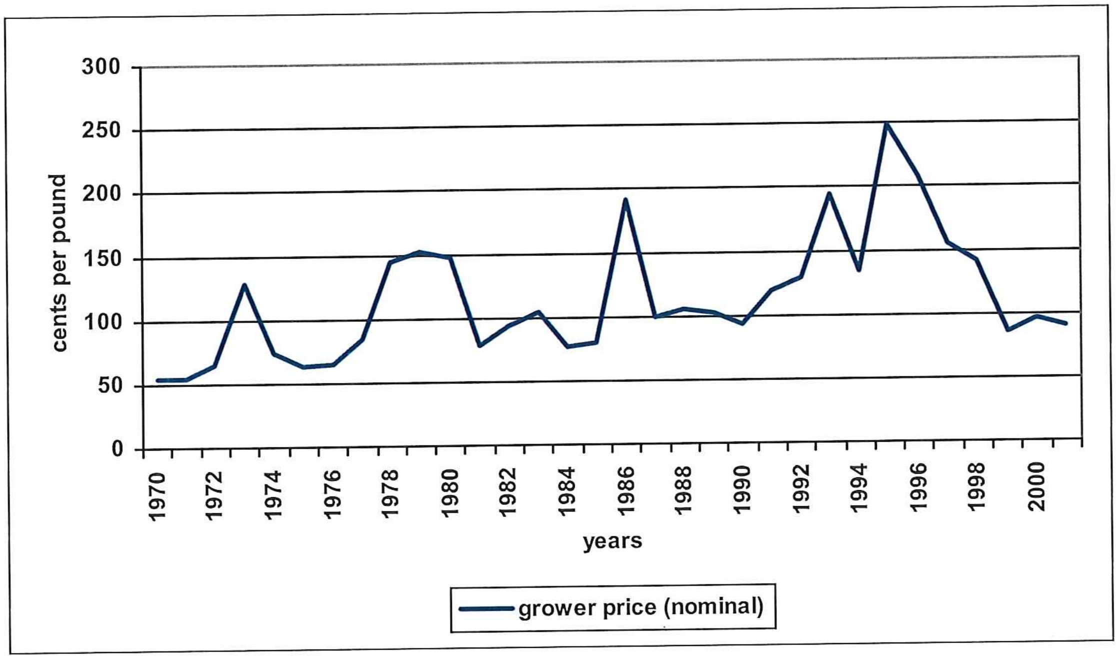

Figure 4A: Grower price for almonds in California (nominal values). Years 1970-2001

Source: USDA

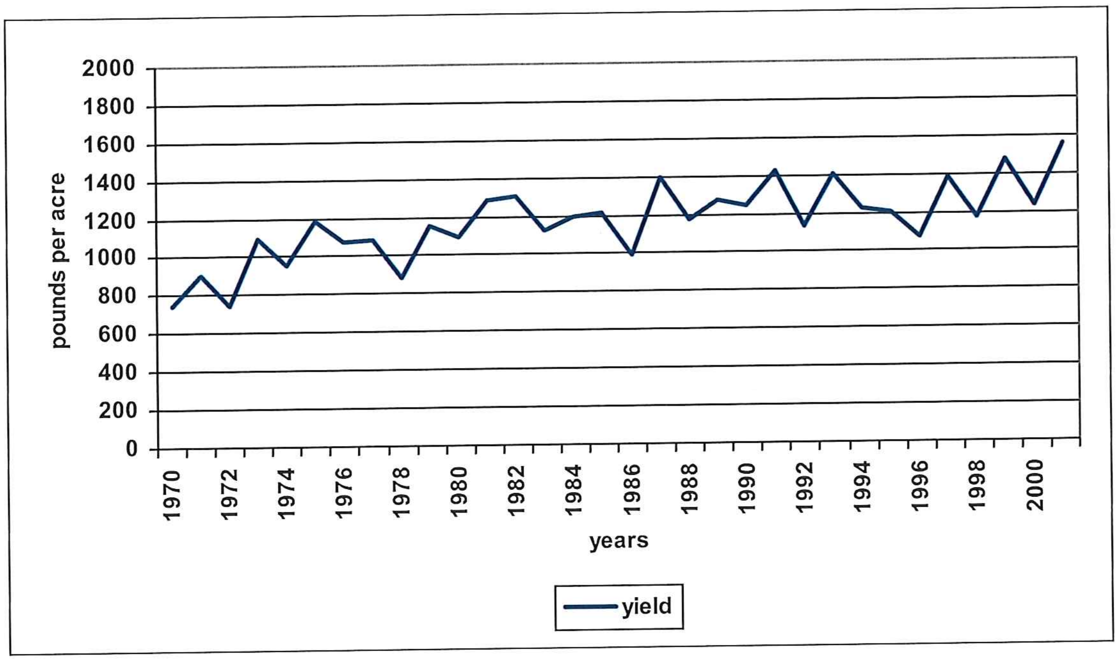

Figure 5A: Yield of almonds in California. Years 1970-2001

Source: USDA

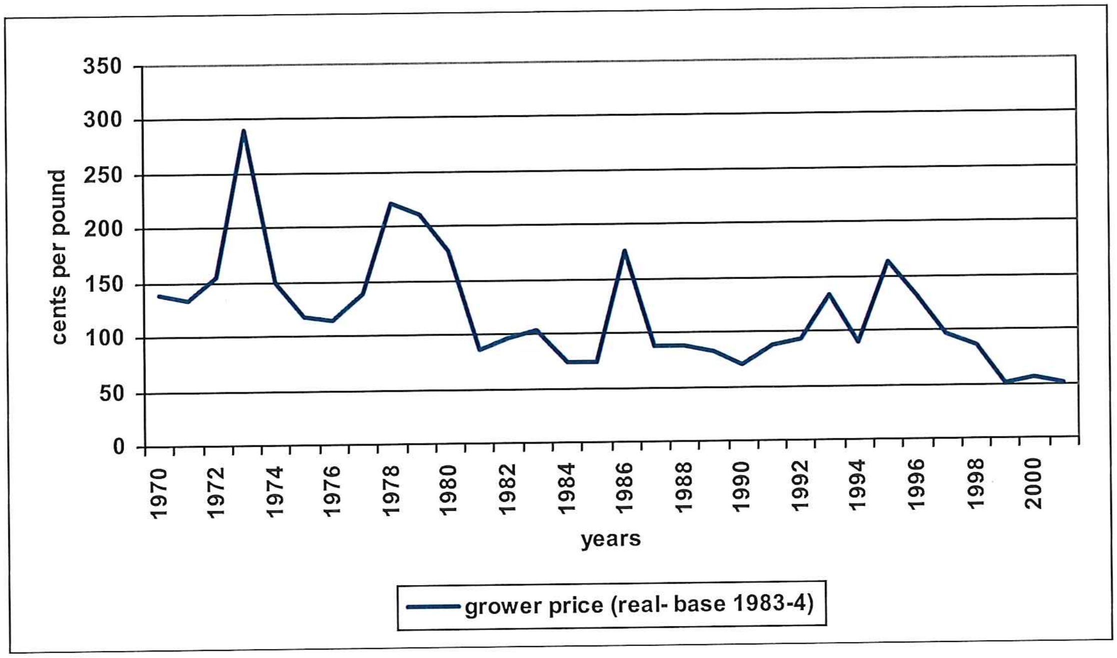

Figure 6A. Real grower price for almonds in California (real values). Years 1970-2001.

Source: USDA