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Allocation-Based Water Pricing Promotes Conservation While Keeping User Costs Low

Ken Baerenklau, Kurt Schwabe, and Ariel Dinar

A Southern California water district reduced household water demand by 10–15% by implementing an allocation-based price structure that did not significantly increase the average price paid for water.

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Special Issue

Climate Change: Challenges to California's Agricultural and Natural Resources

The common approach for pricing water and other goods and services in a market economy is uniform pricing: each unit is priced the same regardless of the amount consumed and the characteristics of the consumer. Block (or tiered) rate pricing is where the cost per unit varies with the amount consumed. Increasing (decreasing) block rates refer to the case when the first units are priced relatively low (high) and subsequent units are priced higher (lower), so that the price per unit rises (falls) with consumption in a stepwise manner. A "volume discount" is an example of decreasing block rate pricing.

Allocation-based water pricing is an innovative type of increasing block rate price structure in which the block sizes vary according to the characteristics of the consumer. Under an allocation-based rate structure, the block sizes are based on household-specific characteristics (e.g., number of residents, irrigated area, unusual circumstances such as medical need), environmental conditions (e.g., evapotranspiration), and a judgment by the water utility regarding what constitutes "efficient" use given those characteristics and conditions. This means that price structures can differ across households at any point in time, and through time for any household. A household's efficient level of use is called its "water budget," and thus, a household that consumes beyond its budget is deemed to be using water inefficiently.

Adoption of Allocation-Based Rates

Allocation-based rates are thought to have significant advantages over uniform and fixed block rate structures. Foremost, allocation-based rates are thought to provide a strong conservation incentive because the block sizes depend on household characteristics. Therefore, all households face higher prices as consumption increases, whereas smaller households rarely enter the upper blocks under fixed block rate pricing. The Irvine Ranch Water District reports that in the 13 years following the introduction of allocation-based rates in the early 1990s, average per-acre outdoor water use declined by 61%.

Allocation-based rates also address equity concerns by providing each household—regardless of size—with a block of low-priced water that should satisfy the most essential uses, such as drinking, cooking and cleaning, while charging higher prices for presumably less essential uses such as landscaping. The highest prices are paid only by those households that exceed their designated water budgets, with already efficient households remaining largely unaffected by the higher rates. Allocation-based rates thus should be more politically acceptable than fixed block rates due to their perceived fairness.

Figure 1. Comparison of Observed Demand Against Model Predictions

Despite these advantages, adoption of allocation-based rates has been relatively slow in California. As of 2011, whereas about half of all utilities had implemented block rate water pricing, only around 25 had adopted allocation-based rate structures. The main concerns appear to be the cost of developing such a rate structure, whether the rate structure will help or hinder efforts to balance revenues with costs, the extent to which the rate structure reduces demand for water, and the differential effects of the rate structure across households.

Demand Reduction Effect

Because multiple competing factors that fluctuate through time influence water demand, the demand effect of a rate structure change cannot be determined simply by observing the effects of introducing a rate structure on demand changes. For example, changes in the broader economy can drive per-capita water demand up or down as prices and incomes fluctuate. Changes in weather and climate, such as cyclical precipitation patterns or regional temperature trends, are important drivers of outdoor water use.

Changes in the availability of, and preferences for, water conserving technologies (such as climate-controlled irrigation systems and low-flow toilets and shower heads) can reduce demand. And even population growth can reduce per-capita demand if new homes must be built with such water-efficient technologies. But of course none of these demand effects should be attributed to the chosen rate structure.

Figure 2. Demand Reduction in Percentage Terms

To properly identify the effect of allocation-based rates on demand, as well as the differential effects across households, we must account for these competing factors. We accomplished this by utilizing household consumption data from the Eastern Municipal Water District of Southern California (EMWD). EMWD is a member agency of the Metropolitan Water District of Southern California and serves a diverse region of western Riverside County that includes the cities of Moreno Valley, Perris, Hemet, Murrieta, and Temecula. This region covers 542 square miles and has a population of more than 768,000. EMWD provides around 90,000 acre-feet of water to approximately 137,000 domestic water service accounts and a much smaller number of agricultural and irrigation users.

EMWD switched from uniform to allocation-based rates in April 2009. The allocation-based rate structure includes four blocks: (1) efficient indoor use, which is primarily a function of household size; (2) efficient outdoor use, which is primarily a function of irrigated area and evapotranspiration requirements; (3) excessive use, which is 50% of the combined indoor and outdoor block sizes; and (4) wasteful use, which accounts for consumption in excess of block 3. The sum of blocks 1 and 2 determine a household's water budget.

In 2008, under uniform rates, the nominal price was $1.85 per 100 cubic feet of water. In 2014, under allocation-based rates, nominal prices ranged from $1.73 for block 1, up to $10.36 for block 4. Both rate structures were designed to balance revenues with costs over the long run.

To estimate the effect of the rate change on household demand, we identified 12,000 single-family households in EMWD's service area with continuous monthly water use

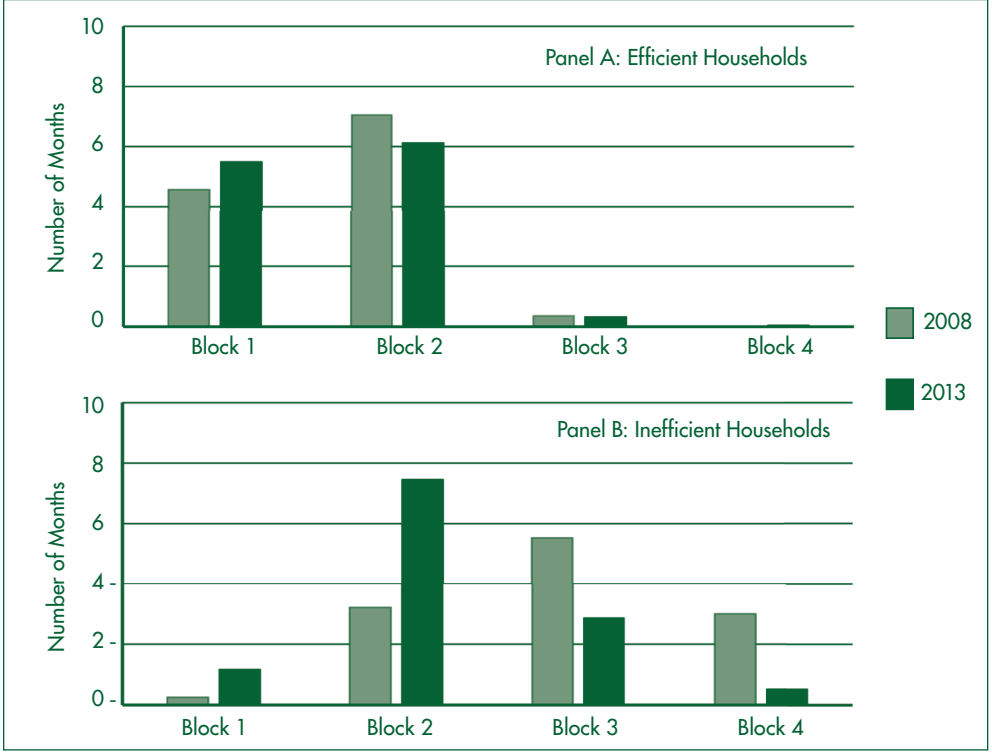
records from January 2003 through April 2014 and no tenancy changes. We used the uniform pricing data from 2003–2008 to estimate a statistical model of household demand that accounts for household size, irrigated area, evapotranspiration requirements, water price, household income, and other relevant factors.

Next we used this model to predict what household demand would have been if EMWD had not switched to allocation-based rates, but had instead maintained uniform rates and set them equal to the average prices paid under allocation-based rates from 2009–2014. We then compared these predictions against observed household demand under allocation-based rates and used the difference between them as an estimate of the demand reduction effect of the allocation-based rates.

Figure 1 shows the results of this comparison for the entire observation period from 2003–2014, using 12-month moving averages to smooth out the seasonal fluctuations in demand. The vertical dashed line corresponds to the change in rate structure in April 2009. To the left of the dashed line, the model performs reasonably well in predicting demand when uniform rates were in effect. But there is a significant divergence between observed and predicted demand to the right of the dashed line, which indicates the introduction of allocation-based rates. Observed demand fell and remained low, while our model predicts that under equivalent uniform rates, demand would have fallen less, levelled off sooner, and climbed back up to about where it was just before the rate change.

The gap that emerges between observed and predicted demand after April 2009 in figure 1 is our estimate of the demand reduction effect of the allocation-based rates. Figure 2 shows this effect in relative terms, again using 12-month moving averages to smooth out the seasonal fluctuations in demand. As the figure shows, one year after the rate change (as of April 2010) there was very little observable effect. But two and a half years after the change, around September 2011, average household water use was about 10% below where it would have been under equivalent uniform rates. Since then, the demand effect has fluctuated but has remained in the 10-15% range for nearly three years.

Figure 3. Marginal Consumption of Efficient and Inefficient Households



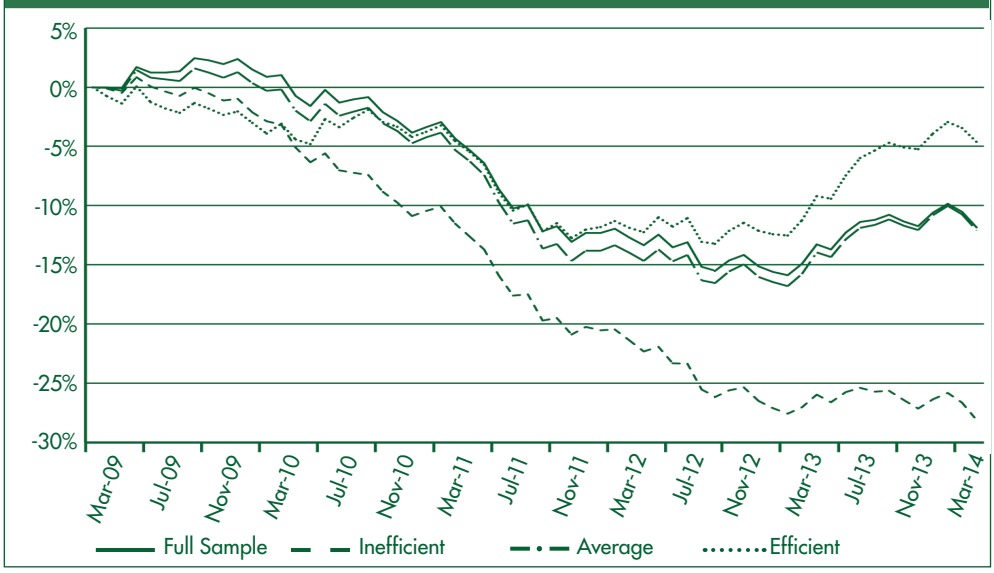
Moreover, the average price paid for water under allocation-based rates rose less than 4% in real terms since April 2009, but our model predicts that a uniform price would have had to rise around 30% to achieve the same observed reduction in demand. This again speaks to the strong conservation incentive provided by this allocation-based rate structure, as well as its cost-effectiveness for households.

Differential Effects Across Households

As with any change in pricing policy, a shift from uniform to allocation-based rates will have differential effects across households. One concern is how such a change may impact lower income households. If such households end up facing significantly higher prices than they did under uniform pricing, concerns about equity and fairness may hinder adoption of allocation-based rates despite their apparent conservation potential. For our sample, this does not appear to be a concern. The average prices paid by households with incomes in the lower third of our sample actually declined under allocation-based rates, but their usage also declined, presumably in response to the threat of higher prices in the upper blocks. These households are now using less water and paying less per unit.

The way in which the estimated demand reduction has been distributed across households is a related question. As mentioned previously, an important motivation for adopting allocation-based rates is the belief that they tend to reduce consumption by inefficient households without penalizing the already efficient households. To assess the extent to which this happened in EMWD's service

Figure 4. Demand Reduction by Efficiency Groups



area, we used EMWD's formula for the volumetric block sizes to estimate water budgets for 2008, before the rate change. We compared the observed consumption of our sample households against these hypothetical water budgets to develop a relative measure of efficiency. We then ranked the households according to this measure and divided them into three groups: efficient (top third), average (middle third), and inefficient (lower third).

Figure 3 (on page 3) shows how the efficient and inefficient households responded to the allocation-based rates. The figure shows the number of months in which marginal consumption for each group was in each of the four blocks. From 2008 to 2013, the efficient households (Panel A) did not alter consumption very much: on average these households consumed within their estimated water budgets (blocks 1 and 2) for more than 11 months in each of these years.

But the inefficient households (Panel B) show a much larger response to the rate structure change. In 2008, these households consumed within their estimated water budgets for less than four months, whereas they did so for more than eight months in 2013. Apparently the allocation-based rates have caused these households to become much more efficient while affecting the already efficient households very little.

Figure 4 shows how the group-specific household demand effects have evolved through time. Not only have the allocation-based rates had a larger effect on inefficient households, but the demand reductions by these households also appear to be more resilient compared to the other groups. The figure shows that the inefficient households are the only group that has not experienced a reduction in the demand effect since 2012, while the demand effect for the already efficient households has decreased significantly from 13% to 5%.

Conclusions

The results of our study suggest that allocation-based rates can be a highly effective and equitable conservation tool for water utilities, although a substantial amount of time is required for the full extent of the demand reductions to be realized. For water utilities that are considering adopting allocation-based rates, this study provides support for doing so, with the caveat that conservation goals may take years to achieve.

Although speculative, the observed time lags could be the result of households gradually learning how to respond to higher marginal water prices by reassessing old water use habits and developing new ones. This also would be consistent with the reduction in observed demand in figure 1, which remains relatively stable even when the predicted demand rebounds significantly. If true, then efforts to promote quicker re-learning of water consumption habits should hasten the attainment of conservation goals, but exactly how to go about doing this is a topic for future work.

A potentially fruitful line of new research would be to investigate the extent to which non-price instruments and/or neighborhood effects influence learning and habit formation. Some water utilities have begun reporting local average water consumption on individual bills to give households a better idea of how their consumption compares to a relevant peer group.

Such information, combined with a high marginal price for "excessive" water use, could prove to be a highly effective approach to encouraging urban water conservation.

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For additional information, the authors recommend:

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Olive Fruit Fly: Timing the Harvest to Manage the Pest

Kelly Cobourn, Emma Knoesen, Hannah Burrack, Rachael Goodhue, Jeffrey Williams and Frank G. Zalom

The olive fruit fly is one of the primary pests of California olives. The choice of harvest date is one tool available to growers for managing economic losses from olive fruit fly infestations. Harvesting earlier reduces losses and requires fewer insecticide applications for managing an infestation. However, harvesting earlier results in smaller olives. Growers face a trade-off between reduced losses and insecticide costs and a higher price per unit sold.

The olive fruit fly is one of the primary pests of olives. Growers can reduce damage and pest management costs by harvesting earlier, but this can also reduce price. The implications of this trade-off vary by region, and differ in terms of growing conditions and cultivar.

The olive fruit fly has been in the news again this season, due to substantial fruit infestations last fall that were reminiscent of those in the mid-2000s. Infestations by the olive fruit fly are a major concern to growers because the fly decreases the quality and yield of fruit. Native to West Africa, the fly has been a longtime pest for olives in the Mediterranean region. It is a relatively recent problem for California growers, with its first detection in 1998. Today, the olive fruit fly is one of the primary pests of California olives.

In this article, we model the impact of infestations on growers' profits. We consider harvest date as an additional tool for the management of damage caused by the olive fruit fly. Its population is dependent on weather factors including temperature, humidity and precipitation, as well as on certain management practices such as irrigation. Olive fruit development is dependent on these same factors, so both costs and revenues are affected by harvest date.

Sources of Economic Damage

The olive fruit fly damages the olive fruit during the fly's reproductive process. A female adult fruit fly lays eggs in the olive fruit, leaving behind a distinguishable mark on the surface of the olive called an ovipositional sting. As the larvae develop inside the olive, they feed on the pulp of the fruit causing the fruit to drop early or rot. Larvae may pupate within the fruit or exit the fruit to pupate in the soil.

The physical damage caused by the olive fly translates to economic damages in several ways. There is little to no tolerance for larval presence in whole canned table olives, and infestation may cause total rejection of a shipment. Fruit damaged by an olive fruit fly may rot more quickly after harvest than uninfested fruit, making them unsuitable for oil production unless they can be crushed immediately following harvest. Finally, infestations occurring late in the ripening period may cause premature fruit drop, directly reducing yield.

Table olive processors in Europe normally have a 1% threshold for damage from the olive fruit fly. In California, table olive processors have zero tolerance because damaged fruit are unacceptable for canning. Olive oil processors usually have a threshold of damage around 10%; damage decreases oil quality by increasing its acidity. Thus, the cost of damage to growers (and the benefit of control) depends on whether they sell their olives for canning or oil. We focus on table olives.

Table olive prices vary by size and cultivar group. Larger fruit is rewarded with a higher price, but larger fruit is also more susceptible to damage by the olive fly. Therefore, the extent and the cost of damage varies for growers depending on the cultivars they produce. Table 1 (page 6)reports the average price by cultivar group and size category for 2000–2010. Group I cultivars tend to be larger and receive higher prices. All else equal, the cost of damage is greater for producers of Group I cultivars.

Available Management Practices

Growers can choose from among several nonchemical and chemical options to limit fruit infestations, either in combination or alone. Field sanitation is one management tool. Removing fallen fruit quickly and harvesting before fruit drop reduces the number of larvae that pupate in

Table 1. Price by Size and Cultivar Group, 2000–2010		
Group and size	Volume (mm3)	Average Price (USD/ metric ton)
Group I: Ascolana, Barouni, Sevillano, St. Agostino		
Cull/ undersize	--	$10.99
Extra-large limited	5,255-6,282	$305.25
Extra-large canning	6,282-7,052	$347.99
Jumbo	7,052-8,336	$911.47
Colossal	8,336-9,363	$9,457.26
Super colossal	>9,363	$972.53
Group II: Haas, Manzanillo, Mission, Obliza		
Cull/ undersize	--	$10.99
Sub-petite	<1,800	$293.04
Petite	1,800-2,608	$421.24
Small	2,608-2,877	$576.92
Medium	2,877-3,415	$115.38
Large	3,415-3,685	$1,133.7
Extra large	>3,685	$1,139.8

Source: Price data provided by the Olive Growers' Council of California (personal communication, Adin Hester, 11 July 2011).

the soil, thus reducing overwintering fly populations that are a source for infestations the next season. Ensuring that no fruit stays on the trees after harvest minimizes the reproductive options available to the flies during the winter. These sanitation methods alone cannot suppress damage to a level acceptable for canning because the fly is highly mobile and can migrate from nearby groves.

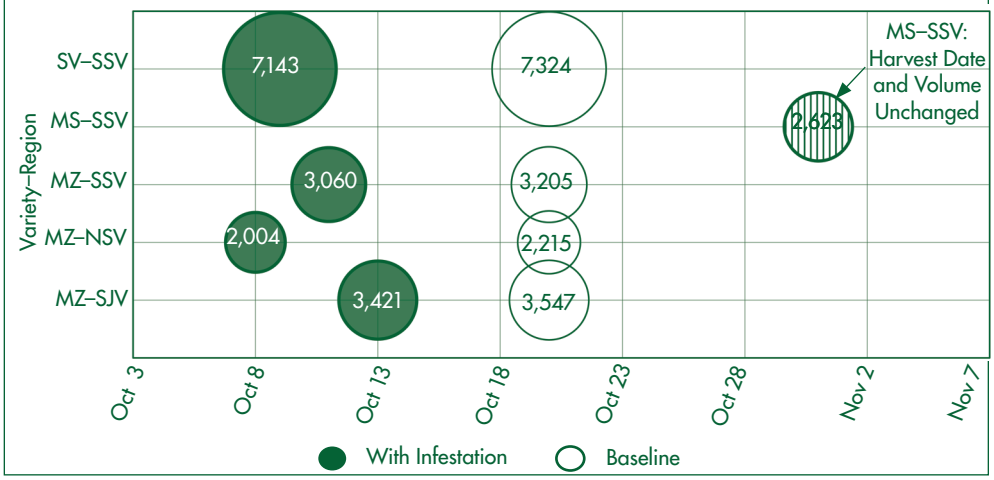
Only a few insecticides have been available in California for managing infestations, including GF-120 NF Naturalyte Fruit Fly Bait (Dow AgroSciences LLC) and Surround (kaolin clay, Englehard Corporation). Both products are certified for use on an organic crop. GF-120 or kaolin clay treatment should begin around mid-June, or earlier depending on location, at pit hardening. Growers must apply multiple applications of GF-120 each season until harvest while Surround must be applied as needed to ensure the fruit remains coated. Growers may now use Danitol (Valent), a pyrethroid. Danitol is normally only used later in the season and in limited amounts per season because its use may result in secondary pest outbreaks.

At this time, options for biological control are limited. While some parasitoids native to California do attack the fly, they are not effective enough to provide control when olive fly pressure is high. Researchers have explored areas in Africa and Asia for a parasitoid of the olive fruit fly that could be imported to California, and have also evaluated parasitoids of other fruit flies to see if they could similarly attack the olive fruit fly. To date, studies are still being conducted on the effectiveness of different parasitoids.

Growers can also shift their harvest date. Because olive fruit flies are more likely to infest large fruit, removing the fruit earlier decreases the likelihood of infestation. However, harvesting olives earlier means they are smaller, while larger olives obtain higher prices (Table 1). About two months before harvest, processors and the Olive Growers' Council of California negotiate to set prices, which allows growers to know the exact return for delivering larger fruit. If there is no chance of infestation, growers can choose an optimal harvest date that balances the increased price received for larger fruit with the risks of over maturation or fruit damage due to freezing. With the added concern of infestation, when choosing a harvest date growers must also consider the cost of insecticide applications and that the risk of infestation increases as olive size increases

In order to analyze the optimal combination of the two pest management strategies of insecticide use and moving the harvest date, we formulate a model of olive production which gives growers two decisions—whether and when to apply insecticide and when to harvest their crop. In the model, the amount of damage due to infestation at any point in the season is determined by insecticide applications. In addition to damage to harvested fruit, infestation impacts the quantity of fruit harvested by affecting premature fruit drop, which, in turn, impacts crop revenue. The harvest decision affects the size of fruit harvested (and the price received by the grower) and the amount of insecticide used.

Figure 1. Harvest Date and Olive Volume With and Without Fruit Fly Infestation



Approach

We identify the profit-maximizing combination of pesticide applications and harvest date in a single season for five growers, differentiated by cultivar and/or production region, with and without an olive fruit fly infestation. The three production regions are the Northern Sacramento Valley (NSV), which includes Butte, Shasta, and Tehama Counties; the Southern Sacramento Valley (SSV), which includes Colusa and Glenn Counties; and the San Joaquin Valley (SJV), which includes Fresno, Kern, Madera, and Tulare Counties. We consider three cultivars: Sevillano (SV), Mission (MS), and Manzanillo (MZ).

The five cultivar-region pairs we analyze are MZ-SSV, MZ-NSV, MZ-SJV, SV-SSV, and MS-SSV. This set allows us to analyze differences in growers' profit-maximizing decisions by geographic regions that vary in climate, as well as differences in decisions by varieties for the Southern Sacramento Valley, which have different potential sizes and belong to different cultivar groups for pricing purposes. Table 2 reports overall acreage and production for the California olive industry. Table 3 shows the distribution of acreage and cultivars across these regions. Comparing Tables 2 and 3, the variety-region pairs considered here represent a significant portion of the California olive industry.

We calculate the amount of fruit damaged on a given day in the growing season depending on any insecticide application. Damaged fruit may drop early and then cannot be harvested. The number of days between damage and fruit drop is not known precisely; we utilize a difference of two weeks. Thus, yield is the number of fruit undamaged by olive fruit flies two weeks before harvest. We then compute profits for each day and its associated damages.

Revenues and costs determine profits while price and damage determine revenue. Undamaged fruit generates revenue, while excessive damage can lead to the rejection of a delivery, resulting in zero revenues. The total cost of insecticide treatments depends on the cost per treatment and the number of treatments applied. Insecticide costs are the only costs allowed to be affected by olive fruit fly infestations.

Table 2. California Olive Industry Data

Year	Bearing Acres	Production (tons)	Total Value ($1,000's)	Quantity Canned (tons)	Percentage Used for Canning	
					In Tons	By Value
2009	31,000	46,300	32,209	4,500	53%	65%
2010	36,000	206,000	136,796	25,000	61%	79%
2011	41,500	71,200	52,168	26,500	37%	54%
2012	44,000	160,000	130,038	78,500	49%	67%

Source: California Department of Food and Agriculture

Results

Figure 1 summarizes changes in the profit-maximizing harvest date and the resulting olive size for all five cultivar-region pairs. The vertical axis lists the cultivar-region pairs, and the horizontal axis represents time. We report two harvest dates: one in the absence of infestation and one when the olive fruit fly is present. The bubbles corresponding to each date represent the olive fruit size at harvest. In the absence of infestation, the optimal harvest date does not vary significantly by cultivar or region. The presence of the olive fruit fly induces differences in the optimal harvest date, which vary by region and across cultivars. Earlier dates are associated with smaller olive sizes as shown in the figure.

We analyze the Manzanillo cultivar for all three production regions. In the absence of an infestation, the profit-maximizing harvest date is October 20 for all regions. An infestation moves the optimal harvest date earlier for all regions, but the time difference varies. The difference is the smallest in the SJV, where the profit-maximizing harvest is seven days earlier. The difference is largest in the NSV, twelve days earlier.

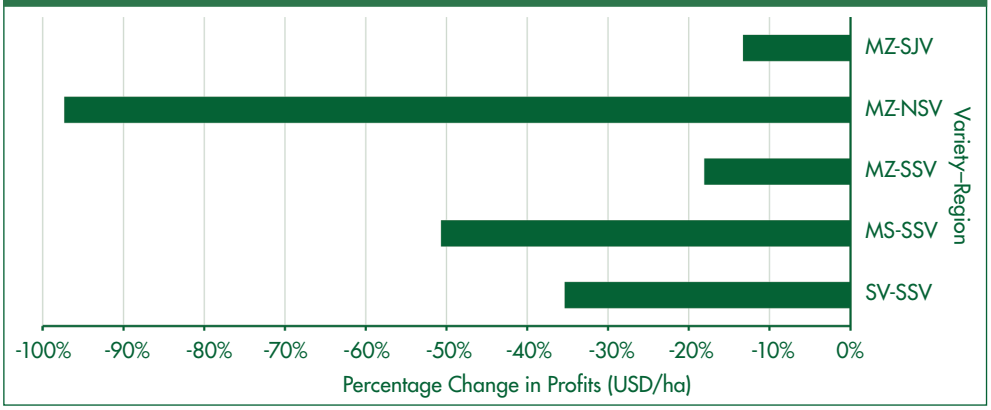
The variation in the effect on harvest date for the same variety is due to differences in weather conditions across regions, which alter olive fruit fly development and olive growth. Earlier harvest dates result in smaller olives. This effect can be seen in Figure 1 by comparing the olive

Table 3. Table Olive Production in Acres, by Cultivar and Region, 2012–13

Cultivar	Acres/Region			
	SSV	NSV	SJV	Total
Sevillano (SV)	446	1,308	560	2,314
Manzanillo (MZ)	3,043	3,142	13,987	20,172
Other	22	277	80	379
Total	3,511	4,727	14,627	22,865

Source: California Olive Committee, 2012

Figure 2. Change in Profits with Olive Fruit Fly Infestation



volumes at the time of harvest with and without an olive fruit fly infestation for each cultivar-region pair.

The three cultivars produced in the SSV also show differences in the profit-maximizing adjustment in the harvest date. The Sevillano has the largest adjustment; the profit-maximizing harvest date is eleven days earlier when the olive fruit fly is present. At the other extreme, the Mission cultivar's profit-maximizing harvest date remains unchanged as shown in Figure 1, by the identical olive volume and date. Mission olives are relatively small and unattractive to the olive fruit fly, so the increased cost of damage is relatively small.

Figure 2 reports the percentage change in profits for each cultivar-region pair. As with the harvest date, the percentage change varies by region and cultivar. For the Manzanillo variety, the decrease in profits associated with an olive fruit fly infestation is largest in the NSV, 97%, while it is only 13% in the SJV. SJV Manzanillo producers benefit more from the ability to adjust the harvest date than producers in other regions, likely due to the more rapid growth of olives, which provides more revenues to offset increased yield loss and damage.

The relative magnitudes of changes in profits do not correspond exactly to changes in harvest date, due to differences in pricing schedules, the growth of olives over time, and the increase in damage over time. This is clearest for the Mission cultivar. While its profit-maximizing harvest date does not change, profits decrease 51%.

Conclusion

The invasion of the olive fruit fly has complicated growers' management decisions. Unlike some pests, damage is influenced by the same factors that influence olive quality (size) and, hence, price. Growers can reduce damage and pest management costs by harvesting earlier, but this can also reduce price. The implications of this trade-off vary by region and differ in terms of growing conditions and cultivar.

This analysis demonstrates that harvest timing can be an important pest management tool for growers in certain situations. Its value, relative to other tools, depends on differences in damage, yield, costs, and price associated with a change in harvest date.

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For additional information, the authors recommend:

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Farm Labor in California's Specialty Crops

Philip Martin

California is the leading farm state because it produces almost half of U.S. fresh fruits and vegetables, many of which are labor-intensive.

The Census of Agriculture (COA), which provides the most complete profile of the nation's farming sector, highlights the importance of fruits and nuts, vegetables and melons, and horticultural specialty (FVH) crops in California. The farm value of U.S. FVH commodities in 2012 was $57 billion or 27% of U.S. crop sales, while California sales of FVH commodities of $26 billion were 87% of California crop sales. The importance of FVH commodities in California has implications for farm labor.

U.S. and California FVH Agriculture

California has a unique agricultural sector that has led the nation in farm sales since 1950 because of the importance of high-value FVH commodities. The COA defines a farm as a place that normally sells at least $1,000 worth of farm commodities a year. Most of the 2.1 million U.S. farms and the 78,000 California farms are part-time, hobby, and retirement operations that lose money farming but survive because of income from nonfarm jobs, social security, and other sources.

The COA reported that over half of U.S. farms, almost 1.2 million or 56%, each sold less than $10,000 worth of farm products in 2012, and they collectively accounted for $3 billion or less than 1% of the $395 billion in total farm sales (Figure 1). At the other end of the farm-size spectrum, the 81,600 U.S. farms that each had farm sales of $1 million or more in 2012, less than 4% of farms, collectively accounted for $264 billion or two-thirds of total farm sales. Most farm commodities are sold by these relatively few large farms.

FVH commodities account for a quarter of U.S. farm crop sales but over 85% of California crop sales. In 2012 California sales of fruits, nuts, and berries were $17.6 billion, vegetable and melon sales were $6.3 billion, and nursery and greenhouse sales were $2.5 billion—for a total of $26.4 billion.

FVH agriculture is similar to general agriculture in having a majority of small producers and relatively few large producers. COA Table 68, for example, notes that the 33,300 California farms classified as fruit and tree nut farms in 2012 had sales of $14.9 billion. Half of these farms, 16,000, each had fruit and tree nut sales of $50,000 or more, and these larger farms had total sales of $14.6 billion, or 98% of fruit and tree nut sales. Similarly, there were 1,200 berry farms with total berry sales of $1.9 billion, but the 530 that each sold $50,000 or more of berries accounted for 98% of berry sales.

Industry publications that report the acreage of individual growers suggest that the ten largest California producers of some FVH commodities account for 10–30% of the state's production of a commodity. For example, *Growing Produce* reported that Grimmway Farms had over 50,000 acres of vegetables in 2012, 5% of the state's vegetable cropland, and the next three largest vegetable growers each had 25,000 acres or more. Thus, the largest four growers accounted for about 15% of the state's vegetable acreage.

Labor Expenses and Employment

The COA asks farmers to report their expenses for hired labor, including the number of workers they hire directly and the cost of wages, payroll taxes, and job-related benefits. In addition, the COA asks for the cost of workers brought to farms by farm labor contractors and other nonfarm businesses that provide workers and sometimes equipment to perform farm tasks. Some 566,000 U.S. farms reported $27 billion in hired labor expenses in 2012, making hired farm labor 8.2% of farm production expenses. Some 217,000 farms (often the same farms that had hired workers directly) reported $6.5 billion in contract labor expenses, 2% of total farm production costs.

Hired labor was a higher share of production expenses in California, where 33,950 farms reported $5.9 billion in hired labor expenses in 2012 (16.6% of farm production expenses). Some 25,100 farms reported $3.4 billion in contract labor expenses (9.5% of farm production costs), making

Figure 1. U.S. Farms by Size and Farm Sales, 2012

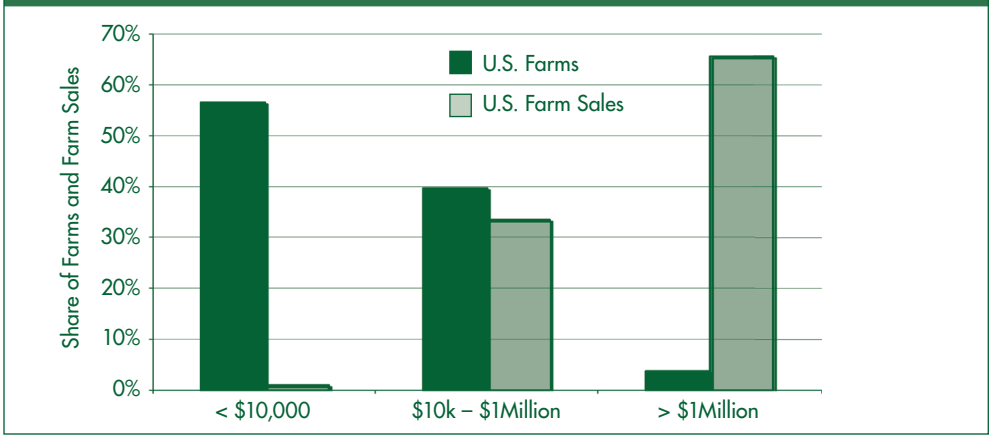
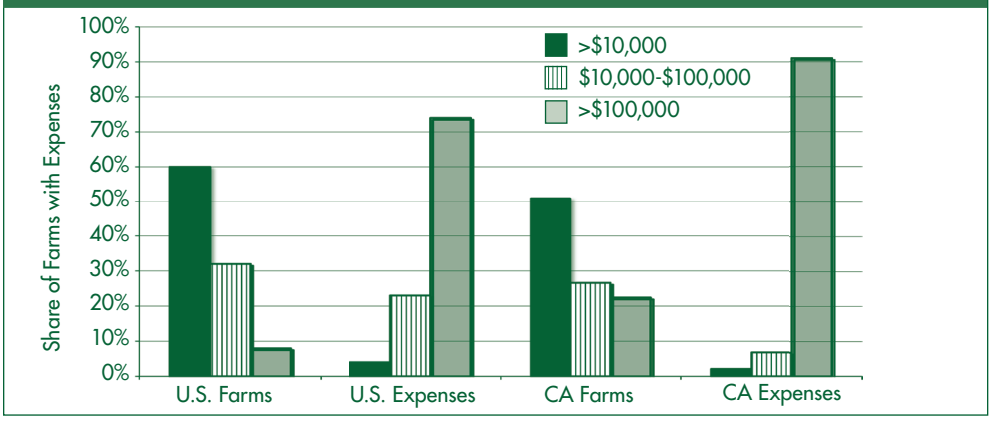


Figure 2. U.S. and California Farms with Hired Labor Expenses, 2012



labor over a quarter of farm production expenses. California accounted for 22% of U.S. hired labor expenses and 52% of U.S. contract labor expenses.

Farm production and farm labor expenses are concentrated on a relatively few large farms. The 44,200 U.S. farms that each paid $100,000 or more for hired labor accounted for 74% of direct-hire farm labor expenses, and the 15,800 that each had $50,000 or more in contract labor expenses accounted for 78% of such expenses. In California, 7,600 farms, less than 10% of the state's farms, each paid $100,000 or more in hired labor expenses and collectively paid 92% of the total, and 6,300 each paid $50,000 or more for contract labor and collectively paid 94% of the total.

In 2012, 60% of U.S. farm employers had less than $10,000 in farm labor expenses, and they collectively accounted for 4% of the $27 billion total. The 44,200 U.S. farms that each had labor expenses of $100,000 or more, 8% of U.S. farm employers, accounted for 74% of total labor expenses. California has a higher share of farms in the more than $100,000 expense-category, but these large farms accounted for over 90% of farm labor expenses.

The COA asks farmers to report how many workers they hired directly, including family members on the farm payroll. In 2012 U.S. farmers reported hiring 2.7 million workers, including 1.7 million who were employed on their farms for less than 150 days, making seasonal workers 60% of individuals hired. Any worker employed seasonally on two farms is counted twice, although there is no duplication of wages in the reporting. California farmers reported 465,400 directly hired workers, including 260,000 or 56% who were seasonal workers.

The biggest concentration of farm workers is on less than one-tenth of U.S. and California farms. The 40,600 U.S. farms that reported hiring ten or more workers accounted for almost 60% of all U.S. farm workers hired while the 7,200 California farms that each hired ten or more workers accounted for almost 85% of the state's farm workers.

The COA reports two more farm labor items. First, it asks farmers if they hired any migrant workers, defined as persons whose farm jobs prevented them from returning to their permanent place of residence the same day. U.S. farmers reported hiring 402,000 migrants directly, making 15% of their hired workers migrants while California farmers reported 119,000 migrants, making 26% of directly hired workers migrants. However, farm employers may not know the permanent residence of their workers.

Second, the COA asks farmers to report the number of unpaid workers on their farms. More U.S. and California farms reported having unpaid workers in 2012, but the number of unpaid workers was lower than the number of paid workers. U.S. farmers reported 2.1 million unpaid and 2.7 million paid farm workers, and California farmers reported 72,000 unpaid and 465,000 paid farm workers.

The COA provides data on farm labor expenses in 2012, but farm worker employment data are reported only for workers hired directly by farmers. Nonetheless, the average number of full-time equivalent jobs in agriculture can be estimated by dividing the labor expenses of farmers by the average hourly earnings of workers to estimate hours worked. If hours worked are divided by 2,080 to get FTE jobs, average farm employment can be compared to average nonfarm employment.

Average FTE agricultural employment in U.S. agriculture estimated in this way rose 14% from 1.2 million in 2007 to 1.4 million in 2012, and average FTE farm employment in California rose 21% from 334,000 in 2007 to 405,000 in 2012. California agriculture is far more labor-intensive than U.S. agriculture. The ratio of farm sales to expenditures for directly hired and contract labor was 11.8 to one for the U.S. in 2012, and 4.3 to one in California.

The number of FTE jobs calculated using total farm labor expenses and average hourly earnings can be compared to average farm employment reported by farm employers when they pay unemployment insurance (UI) taxes. Only larger farm employers must cover their workers under UI programs in many states, and national UI-covered agricultural employment averaged 1.2 million in 2012, about 86% of FTE employment estimated using COA data. In California, where all farm employers who pay at least $100 in quarterly wages must participate in the UI program, UI-covered agricultural employment averaged 411,740 in 2012, slightly more than estimated using COA data.

Clearly, average agricultural employment is not a count of farm workers. Defining a farm worker as a person employed for wages in agriculture

sometime during the year, there were about 2.5 million hired farm workers when USDA analyzed a December supplement to the Current Population Survey that was discontinued in the late 1980s, suggesting two farm workers per FTE or year-round job.

In California, a special analysis of all Social Security Numbers reported by the state's agricultural employers found a million unique SSNs in 2001, when average employment was 388,000, suggesting 2.5 workers per job. The number of workers employed sometime during the year exceeds average employment in seasonal industries with employment peaks and high turnover such as agriculture.

Table 1. U.S. and California Labor Expenses and FTE Jobs, 2007 and 2012

	U.S.			CA		
	2007	2012	Change	2007	2012	Change
Farm Sales ($bil)	297	394	33%	33.9	42.6	26%
Labor Expenses ($bil)	26	34	29%	7	10	34%
Sales to Expense ratio	11.4	11.8	3%	4.6	4.3	-6%
Average Hourly Earns ($)	10.21	11.52	13%	10.51	11.64	11%
Hours worked (mils)	2,547	2,908	14%	695	842	21%
FTE Jobs (2080 hrs)	1,224,290	1,398,070	14%	333,931	404,771	21%

Source: Census of Agriculture and Farm Labor, 2007 & 2012
Labor expenses are for directly hired workers and contract labor

FVH Agriculture and Labor

The COA reports hired and contract labor expenses of farms by their NAICS code or primary commodity. FVH farms were 14% of U.S. farms with direct-hire labor expenses in 2012, but they accounted for 39% of labor expenses. Almost half of all U.S. farms that had labor expenses of $250,000 or more were FVH farms, but the COA does not publish the labor expenses of these large FVH farm employers, so their share of farm labor expenses is unknown. The contract labor picture is similar. FVH farms throughout the U.S. were 21% of farms with contract expenses, account for two-thirds of contract labor expenses, and were 56% of farms with over $50,000 in contract labor expenses in 2012.

Labor expenses are even more concentrated on FVH farms in California. Two-thirds of California farms with labor expenses and 57% of California farms that had labor expenses of $250,000 or more produced FVH commodities, and these farms accounted for 76% of labor expenses for workers hired directly by farmers. FVH farms were 80% of those with contract labor expenses, and they accounted for 93% of contract labor expenses. Over 85% of farms with more than $50,000 in contract labor expenses produced FVH commodities. The share of contract to total farm labor expenses averaged 41% for FVH farms, ranging from 8% for greenhouse and nurseries to about 45% for fruits and vegetables.

California dairy farms, which spent $635 million on hired labor in 2012—over 90% for directly hired workers. Half of the dairies spent more than $250,000 on hired farm workers, and a quarter hired workers via contractors. FVH farms and dairies combined accounted for 86% of California's labor expenses for directly hired workers in 2012 and 94% of contract labor expenses. USDA reports labor data for seven crops and seven livestock commodities, from grains and cotton to beef and poultry, but in California four commodity groups account for almost all farm labor expenses.

Conclusions

The importance of FVH commodities in California agriculture makes the state the leader in farm sales. Farm production and farm worker employment are concentrated on a relatively few large farms across the U.S. and in California, and estimates using COA data suggest that average farm employment is expanding faster in California than in the United States. In California, four of the 14 commodity groups for which the COA reports labor expenses, vegetables and melons, fruits and nuts, greenhouses and nurseries, and dairies, accounted for 86% of farm labor expenses in 2012.

Farm labor is often in the headlines, as exemplified by reports of farm labor shortages due to fewer newcomers from Mexico, unemployment in farm worker communities due to the drought, and the July 1, 2014 increase in the California minimum wage from $8 to $9 an hour. The COA, which provides the most complete profile of the state's agriculture, suggests that farm employment is growing and will continue to garner media attention.

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For additional information, the authors recommend:

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