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Managing a pest with harvest timing: implications for crop quality and price

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Abstract

This article examines a case in which growers' pest management decisions collectively generate a change in price that reduces the losses from infestation for some but further harms others. Olive growers in California control the olive fruit fly not only by spraying insecticides but also by harvesting olives earlier, sacrificing quality and altering the industry's fruit quality distribution. Growers of higher quality fruit alter harvest timing the most, benefiting from the resulting change in the quality premium at the expense of growers of lower quality fruit. Across the industry, the change in the quality premium leads to greater reliance on chemical control.

Keywords: pesticides, quality premium, market response, olive fruit fly

JEL classification: Q12, Q11, C61

1. Introduction

When managing a pest, agricultural producers often have a choice among a number of control methods, both chemical and cultural. This paper analyses the incentives that heterogeneous growers face in deciding whether to mitigate pest damage by applying an insecticide or by shortening the crop's growing season in order to reduce the susceptibility of the host. We demonstrate that when many growers choose to shorten the growing season, the aggregate average quality of the crop decreases. The consequence is that processors' willingness to pay for the crop shifts such that the reward for quality increases. The change in the premium for quality redistributes welfare towards those growers producing a higher quality crop and reduces the incentive for all growers to engage in cultural control, leading to an increased reliance on chemical control.

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Any pest control practice may influence the quantity or quality of a commodity produced. Studies documenting this effect for cultural control include Hubbell, Marra and Carlson (2000) and Qaim and Zilberman (2003), who find that the adoption of Bt cotton enhances yield, and Babcock, Lichtenberg and Zilberman (1992), who find that pruning practices increase apple yield and quality. If a sufficient portion of an industry's growers adopt such practices, their actions may collectively affect the market. For example, White and Wetzstein (1995) demonstrate that when the adoption of integrated pest management (IPM) for cotton increases private net returns by increasing yield and reducing pest control costs, the consequence is an increase in land planted to cotton and a decrease in price. As a result, the benefits to IPM erode as more producers adopt it. Similarly, Pray *et al.* (2002) consider the price effects of the boost in cotton yield and present evidence that increased adoption of Bt cotton depresses prices, attenuating the benefits of adopting the cultivar.

In this literature, producers are often assumed homogeneous, in which case these market-level effects fall evenly upon them. Numerous studies recognise that heterogeneity in pest damage and pest control incentives exists across growers (e.g. Lichtenberg, Parker and Zilberman 1988). The implications of grower heterogeneity for the market-level effects of pest control decisions, particularly for cultural control, have received less attention in the literature. Furthermore, existing studies focus primarily on the welfare implications of changes in yield rather than crop quality. This article focuses on the market effects of quality changes driven by private pest control decisions over both chemical and cultural control practices.

Issues with quality and producer heterogeneity have been explored in a different context by James and Alston (2002) and Crespi and Marette (2003). These studies, which examine the market-level effects of implementing a uniform tax on a good with distinct grades, show that a uniform assessment for advertising on a differentiated product may generate greater gains for some producers than others. This is precisely what we demonstrate within the context of a pest management problem: growers' choices of control activities collectively drive a change in aggregate production, but the welfare gains and losses for each are determined by where an individual producer's crop falls in the industry's quality distribution.

We examine this issue within the context of the olive fruit fly infestation in California. The economic structure of the olive processing industry and the nature of the pest–host relationship combine to create a tradeoff between the length of the growing season and insecticide use. This situation for olives is similar to the case of pink bollworm considered by Harper and Zilberman (1989). However, there is an added dimension in the olive problem because of the role that the quality of fruit plays in the damage process and in determining price received in the processing market. When olive growers extend the season, their fruit grow larger. Processors reward greater size with a price premium. However, as fruit grow in size, they become more susceptible to infestation.

This relationship between size and infestation is explored by Cobourn *et al*. (2011), who document the simultaneous nature of the host growth and pest damage process for olives grown in untreated orchards in California. Their study demonstrates theoretically how the size–damage relationship may influence the damage control practices undertaken by producers, but it does not explore the form of those decisions or their market-level consequences. We build on their study, incorporating the relationship between olive size and pest damage into a dynamic mathematical programming model that optimises day-by-day insecticide use and harvest timing across heterogeneous olive growers. Our results illustrate that substantial heterogeneity in treatment incentives exists among growers. Differences in the tradeoffs between harvest timing and insecticide use arise due to differences in cultivar and climate, which affect the pest–host damage relationship and the rate at which fruits grow.

Though substantial differences exist across growers, nearly all growers choose to harvest earlier as a result of the infestation. Doing so reduces insecticide use by up to 15.25 per cent, depending on the cultivar and location. It also substantially reduces the average quality of fruit produced across the industry. In the second portion of this article, we include the effect of this change in quality on the price premiums paid by processors for higher quality olives. With endogenous prices for raw olives, a decrease in average quality generates an increase in the price for larger fruits and a decrease in the price for smaller fruits. Accounting for this endogenous price change reduces the incentive to substitute changes in harvest timing for chemical control. We also find that growers of the highest quality fruit, who play the dominant role in driving the industry price change, benefit the most from the resulting shift in prices. In contrast, growers of the lowest quality fruit have little to gain from a change in harvest timing, contribute least to the change in average quality, and suffer the most from the endogenous change in price. This redistribution in welfare from low- to high-quality growers is driven in part by biological limitations: it is always possible for growers to reduce the quality of their crop to mitigate pest damage, but crop biology limits the extent to which some growers can capture an increased price for a higher quality product.

2. Controlling infestation in the olive industry

As the olive fruit fly (*Bactrocera oleae*) spread quickly throughout California during the last decade, commercial olive growers employed two strategies to control infestation – regular applications of a registered insecticide or truncation of the growing season. Prior to the arrival of the fly, there were no registered pesticides for olives that could be used to combat fly infestation. Today, two pesticides are registered with the California Department of Pesticide Regulation. GF-120 Naturalyte Bait (Dow AgroSciences LLC) is the most widely used by commercial producers, accounting for over 99 per cent of all chemical applications to olives in the state (California Department of Pesticide Regulation, 2008). GF-120 is a spinosad bait formulation, which has been used to control a number of fruit flies in the family Tephritidae (Prokopy *et al*., 2003; Stark, Vargas and Miller 2004; Pelz *et al*., 2005).[1] The second registered pesticide is Surround WP (Engelhard Corporation), a kaolin clay formulation. Surround is not widely used by commercial olive producers primarily because application is difficult and time-consuming (fruit must be completely covered by a film of clay for the pesticide to be effective).

Because olive trees are a long-lived perennial, truncation of the growing season equates to shifting the timing of harvest.[2] Flexibility in the harvest date arises from the characteristics of olive fruit and the structure of the US olive canning industry. In particular, the olive crop reaches a stage of biological maturity sufficient for harvest prior to traditional harvest dates, but continues to increase in size thereafter.[3] Larger fruit receive a price premium in the canning market, which accounts for the vast majority of US olive production.[4] Given a specific cultivar, the size of the fruit is the dominant quality characteristic considered by canners. For each growing season, an industry price menu specifies price by size and cultivar group, where each group contains several individual cultivars.[5] Table 1 presents summary statistics for prices from the 2000–2010 growing seasons. The premium for the largest olives is substantial, on the order of a factor of 3.

Prior to the olive fruit fly infestation, the optimal timing of harvest balanced the gain in value of the crop due to increased size with losses due to overmaturation and the risk of freeze damage late in the growing season. The arrival of the fly has introduced an additional cost to delaying harvest, namely the increase in the fruit's susceptibility to fly damage as it increases in size. As a growing season progresses and olives become larger, growers must apply GF-120 to suppress damage to a level acceptable in the processing market. Alternatively, growers could harvest earlier, which reduces pest damage and insecticide costs, but entails sacrificing size and associated premiums paid by processors.

Table 2 displays land area in canning olives, by cultivar and producing region for 2009–2010 (California Olive Committee, 2010). Counties are divided into three regions based on location and climate, illustrated in

1 Spinosad poses little risk to human and environmental health (Revis, Miller and Vargas 2004) and is certified for use in organic production.

2 We consider only mature trees, for which there is no planting decision. The land area planted to olives has been constant over the past several decades (USDA-NASS, 2011); this stability suggests that planting decisions play a relatively minor role in industry dynamics.

3 Even as of traditional harvest dates, the olives have not yet ripened. To produce black-ripe olives (the predominant canning style in the US), processors store raw olives in acid baths and then turn them black by pickling them in lye.

4 California is the only state with commercial canning olive production.

5 Delivered olives are sorted and graded by state inspectors as per USDA guidelines. Revenue for a delivery depends on the count per unit weight and total weight of fruit in each size grade (USDA-AMS, 2013b).

Table 1. Price by size and cultivar group, 2000–2010

Group and size	Count (number/kg)	Diameter (mm)	Volume (mm^3)	Price (USD/metric ton) Average	Price (USD/metric ton) Standard deviation
Group I: Ascolano, Barouni, Sevillano, St Agostino					
Cull/undersize	–	–	–	10.99	–
Extra-large limited	165–194	18–20	5,255–6,282	305.25	24.32
Extra-large canning	143–165	20–22	6,282–7,052	347.99	34.67
Jumbo	101–143	22–24	7,052–8,336	911.47	273.15
Colossal	71–101	24–26	8,336–9,363	957.26	199.96
Super colossal	<71	>26	>9,363	972.53	190.23
Group II: Haas, Manzanillo, Mission, Obliza					
Cull/undersize	–	–	–	10.99	–
Sub-petite	>397	<13	<1,800	293.04	98.06
Petite	309–397	13–16	1,800–2,608	421.24	26.21
Small	280–309	16–17	2,608–2,877	576.92	121.52
Medium	231–280	17–19	2,877–3,415	1,115.38	223.21
Large	198–231	19–20	3,415–3,685	1,133.70	204.08
Extra large	<198	>20	>3,685	1,139.80	196.90

Notes: US Department of Agriculture (USDA) size categories are specified based on a count of fruit per pound (converted here to fruit per kilogram) or average diameter (USDA-AMS, 2013a, 2013b). Volume ranges estimated based on the correlation between olive diameter and volume (unpublished data set). Price data provided by the Olive Growers' Council of California (personal communication, Adin Hester, 11 July 2011).

Table 2. Hectares in table olive production in 2009–2010, by cultivar and region within California

	Region			
Cultivar	SSV	NSV	SJV	Total
Sevillano (SV)	347.6 (3.0)	1,142.8 (9.9)	299.9 (2.6)	1,790.3 (15.5)
Manzanillo (MZ)	1,378.8 (11.9)	1,392.5 (12.0)	6,669.2 (57.6)	9,440.5 (81.6)
Other	12.5 (0.1)	279.6 (2.4)	49.8 (0.4)	342.0 (3.0)
Total	1,738.9 (15.0)	2,815.0 (24.3)	7,018.9 (60.6)	11,572.8

Source: California Olive Committee (2010).
Notes: Per cent of total land area in canning olives is in parentheses. SSV, NSV, and SJV denote the Southern and Northern Sacramento Valley and the San Joaquin Valley. Sevillano olives are in Group I; Manzanillo olives are in Group II. 'Other' olive cultivars from Group I include Ascolano and Barouni; from Group II, Mission and Obliza.

Figure 1. The Northern Sacramento Valley (NSV) includes Butte, Shasta, and Tehama County; the Southern Sacramento Valley (SSV) includes Colusa and Glenn County; the San Joaquin Valley (SJV) includes Fresno, Kern, Madera, and Tulare County. The top canning olive-producing counties are Tulare, Tehama, and Glenn County, which are home to 89.2 per cent of the state's land area in canning olives and 88.6 per cent of the total value of production. Manzanillo olives (Group II) are the most popular fruit grown for canning in California, accounting for 81.6 per cent of the total land area in canning olives. Group I olives (Sevillano) are larger than Group II olives and account for less of total production statewide.

In the California canning olive industry, heterogeneity among growers arises due to differences in cultivar, growing region, and industry price schedule. Cultivar type drives differences among growers because cultivars range widely in size and fly damage susceptibility. The growing region plays a key role because weather conditions affect the olive fly's prevalence. Finally, the price schedule specifies differing size premiums by cultivar type, and price premiums affect the incentives of individual producers to alter harvest timing. The substantial heterogeneity that exists between olive growers in California forms the basis for this empirical analysis. Two additional characteristics of olive production in California further simplify our empirical analysis. First, and most significant, olive trees are effectively a single-pest host and the olive fruit fly is a single-host pest. Prior to the arrival of the olive fruit fly, olive trees had few pests, all of which could be controlled with pruning. The olive fruit fly damages olives during reproduction and reproduces only on olive fruit. The fly has not been found to affect any other host through feeding or reproductive activity. Thus, any spraying on other crops is not relevant. Second, the potential for substitution between cultivars or with other crops is limited due to the long-lived nature of olive trees and the areas in which it is produced, which are unsuitable for many other crops.

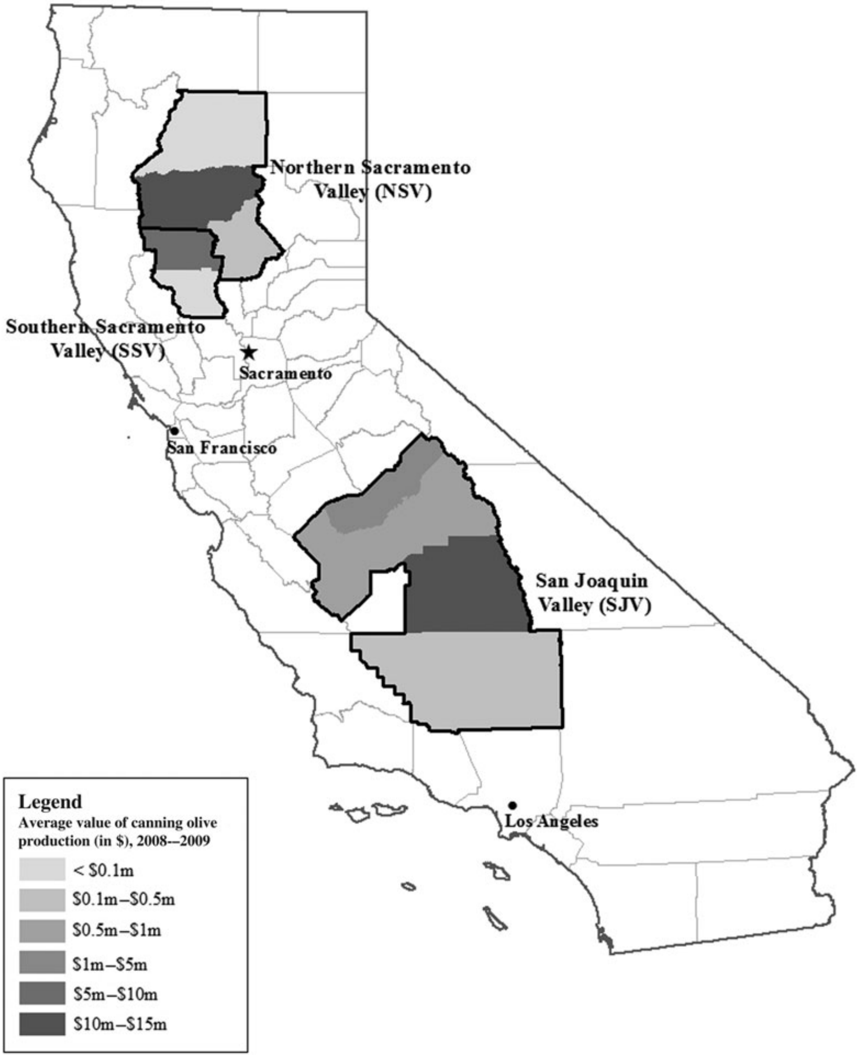

Fig. 1. Olive-producing regions and the average value of canning olive production by county, 2008–2009.
Notes: All un-shaded counties report zero canning olive production (California Olive Committee, 2010).

3. Growers' decisions about harvest timing and insecticide use

To examine individual grower's decisions about pest management, we formulate a dynamic intra-seasonal model of olive production. A grower faces two decision variables in the model – whether to apply an insecticide and when to harvest the crop. The decision on insecticide use determines the proportion of the crop that is damaged by fly infestation, which affects the quantity of fruit harvested and sold. The harvest timing decision also affects insecticide use and quantity produced, but most immediately affects the size of fruit harvested. By choosing a harvest date, growers choose the optimal size of their fruit at harvest and the per-unit price received in the processing market.

We limit our attention to a single growing season because fly infestation has no impact on the long-run productivity of olive trees. Damage affects only the production of fruit in a single season, which implies that seasons are not linked dynamically by the pest damage process. The biology of the fly also suggests that a one-season planning horizon is appropriate for individual growers. Specifically, the fly reproduces very quickly, completing four to six generations per year, and is highly mobile. Regardless of the local population carryover between seasons, rapid population growth coupled with in-migration implies that growers will likely consider one season at a time when choosing pest control strategies.[6]

Uncertainty is always a potential element of a model, particularly when economics is integrated with biology. Even so, the focus of this paper is on how heterogeneity among growers of olives affects price, pest management incentives, and the losses from infestation. In order to focus on the implications of heterogeneity, we assume that individual growers operate under certainty. Qiao *et al*. (2009) and Marsh, Huffaker and Long (2000) similarly assume certainty in dynamic optimisation models of pest management. Heterogeneity among growers is key to the analysis because it implies that individual growers produce fruit that sits at different points along the industry's fruit quality distribution. Any change in the premium for size that arises from collective changes in pest management practices affects growers differently depending on where they fall along that distribution. It is this difference among growers that drives the model and our conclusions, not the uncertainty within each grower's optimisation problem.[7]

3.1. Dynamic optimisation model of pest management decisions

We model individual-level decisions for five representative growers. Each grower is a dynamic optimiser who accounts for the effect of today's treatment

6 Fly population carryover may be limited by sanitising the orchard after harvest and disking the orchard floor, but neither method is sufficient to eliminate infestation in the subsequent season. Because flies winter in unknown locations, there is no means of eliminating all residual flies. Although some evidence suggests that the olive fruit fly is building a resistance to GF-120, we do not expect individual growers to account for the external costs associated with the development of resistance when choosing their pest control activities for a season, nor do individual growers account for spatial externalities within a season. The choice to harvest earlier in one orchard has no impact on the infestation rates observed in other orchards. While the decision of whether to sanitise the orchard after harvest can affect other orchards, not enough information is available to model this effect.

7 To test the validity of the certainty assumption, we expanded the model to incorporate uncertainty over the level of pest damage and solved each grower's dynamic optimisation problem with fixed and flexible harvest timing. The incorporation of uncertainty has little effect on optimal harvest timing decisions. As a result, the aggregate quantity and quality of fruit produced in the industry and prices are similar to that in the certainty model, and our conclusions related to the effects of price endogeneity are unchanged. Results are available upon request.

decision on fly damage in future periods and on yield and fruit size at harvest. The five growers are defined by region of production and cultivar type and are chosen to correspond to the prominent production activities within California. The grower types are also chosen to allow a within-region comparison across growers of different cultivars and an inter-regional comparison across growers of the same cultivar.

An individual grower chooses insecticide applications and the date of harvest to maximise discounted profit over the growing season:

$$\max_{u_t, T} \beta^T [p_g(v_{iT}|Q_g, V_g)y_{iT} - H] - \sum_{t=0}^{T-1} \beta^t c u_{it}, \tag{1}$$

where i indexes the representative grower, g indexes the cultivar group, and t indexes the day of the growing season. In expression (1), u_t denotes insecticide applications by day, T is the date of harvest, p_g is the per-unit price for raw olives in cultivar group g, v_{iT} is the size of fruit at harvest, Q_g is the aggregate quantity of fruit produced by growers in cultivar group g, V_g is the average size of fruit produced by growers in cultivar group g, y_{iT} is the fruit yield at harvest, H is the harvest cost, and c is the cost of an insecticide application. The discount factor is $\beta = (1 + r)^{-1} < 1$, where r is the interest rate. We assume that growers manage their orchards optimally with respect to inputs other than the insecticide and harvest timing, and that pest management decisions are separable from decisions regarding other inputs.

Growers' profit consists of two terms: the first term in objective function (1) captures revenue and harvest costs realised at harvest; the second term captures the net present value of insecticide application costs over the growing season.[8] Revenue at harvest depends on the size of the crop, which determines the per-unit price received from processors. The per-unit price also depends on aggregate quantity and quality produced by all growers within a cultivar group. These arguments are included to indicate that the price schedule for a cultivar group in any given season is conditional on aggregate output. From an individual grower's perspective, the price menu is exogenous, though growers may influence where on the price menu their fruit fall by manipulating harvest timing.

The average size of fruit on any day of the growing season is a function of temperature, humidity, and precipitation. Fruit size does not depend on fly damage or the use of the insecticide. This is consistent with entomological studies of the infestation in California, which indicate that fruit continue to grow at the same rate after a fly stings the fruit for reproduction. The fruit

8 For simplicity, harvest costs enter expression (1) as though all harvesting takes place on a single day. In practice, an individual harvest may take several weeks because olives must be hand-harvested and because of local labour constraints, e.g. a 40.5-ha orchard requires 25 days for 48 workers to harvest (Sibbett and Ferguson, 2005). The decision to harvest involves setting a start date and harvesting fruit as quickly as possible thereafter. When solving for the harvest timing decision, we assume that the grower chooses the optimal first date of harvest. Any change in harvest timing can be thought of as a shift in the harvest window.

size model is from Cobourn *et al.* (2011):

$$v_{it} = \alpha_{0i} + \alpha_{1i}\mathrm{HD}_{it} + \alpha_{2i}\mathrm{PR}_{it} + \alpha_{3i}\mathrm{CD}_{it} + \alpha_{4i}\mathrm{CD}_{it}^2 + \alpha_{5i}\mathrm{CD}_{it}\mathrm{HD}_{it}, \quad (2)$$

where HD denotes humidity, PR denotes precipitation, and CD denotes cumulative growing degree-days. We estimate the parameters of equation (2) for each grower, using an empirical data set collected by entomologists throughout the 2005 growing season. We combine the estimated parameters of equation (2) with publicly available weather data from 1989 to 2008 for each region to project fruit size under average weather conditions.[9]

Baseline damage ($d^{\max}$), the amount of damage that would occur without any insecticide use, is a function of fruit size and temperatures, and accelerates late in the growing season. The baseline damage model is also from Cobourn *et al.* (2011):

$$d_{it}^{\max} = \delta_{0i} + \delta_{1i}v_{it} + \delta_{2i}v_{it}\mathrm{LT}_t + \delta_{3i}\mathrm{CO}_{it} + \delta_{4i}\mathrm{CO}_{it}^2 + \delta_{5i}\mathrm{CO}_{it}\mathrm{LT}_t, \quad (3)$$

where LT is an indicator for dates after 1 August, and CO denotes cumulative days with temperatures outside of adult fruit fly activity thresholds. The parameters of equation (3) are estimated empirically using the same data set used for equation (2). The same weather data are used to project baseline damage rates by cultivar and region.[10]

The proportion of fruit damaged on day t, denoted d, is given by:

$$d_{it} = d_{it}^{\max}(1 - \theta u_{it}), \quad (4)$$

where θ is the efficacy of the insecticide, expressed as a proportional reduction in the baseline damage rate. We specify u as a binary control variable equal to 1 if the crop is treated with GF-120 on day t. A binary specification is consistent with the fact that growers are often constrained to apply insecticide treatments at the manufacturer's recommended rate due to liability issues (Swinton and King, 1994). GF-120 remains at least partially effective for a number of days after an application. However, the rate at which its efficacy deteriorates depends on weather and the proximity of the nearest untreated and infested olive tree. Instead of specifying an interval over which the insecticide remains effective, we determine whether treatment is optimal for each day of the growing season. In so doing, we identify the range of dates over which the grower optimally applies the insecticide, as well as the total number of treatment days.

Though fly damage does not penalise fruit growth, it does induce fruit drop, which reduces yield by causing infested fruit to fall from the tree before

9 Based on the empirical data set, the distribution of fruit sizes for each grower considered in the simulation model is approximately normal and the standard deviation across growers within a cultivar group is similar. Average fruit size is therefore a suitable descriptor of heterogeneity among growers' crops.

10 The estimated parameters of equations (2) and (3) are not reported here for brevity. They are available upon request.

harvest. The amount of time between when fruit are infested and when they drop is unknown and varies with the weather. We assume that fruit drops k days after it is first damaged. Thus, the cumulative proportion of fruit damaged up to k days before harvest reduces yield from its potential level with no infestation. Yield at harvest is given by:

$$y_{iT} = y_{iT}^{\max}\left(1 - \sum_{j=0}^{T-k} \mathrm{d}_{ij}\right), \tag{5}$$

where $y^{\max}$ is the potential yield, or the yield that would be obtained under prevailing weather conditions with no pest damage.

The primary factor that determines the potential yield is fruit set at the beginning of the season. Fruit set depends on weather, management practices unrelated to the pest (e.g. nitrogen management and pruning), and the alternate-bearing nature of olive trees. We model potential yield as a parameter that follows a quadratic trend over the growing season, increasing through late October and decreasing thereafter. The potential yield trajectory is calibrated to reflect yields reported by Sibbett *et al*. (1986). As per the literature on olive pomology, yield does not depend on fruit size: over the viable harvest period for olives, yield (in metric tons per hectare) reaches a plateau while the size of fruits continues to increase (Sibbett and Ferguson, 2005). Though increasing in size, olives lose water content as they mature, which offsets gains in size to keep weight fairly constant.[11]

In addition to penalising yield and/or requiring costly insecticide applications, infestation may generate losses by threatening a grower's ability to meet fly-damage thresholds set by canning processors. Processors in the industry have, to date, enforced tolerance thresholds for damage based on the proportion of a delivery with observed ovipositional stings, which render the fruit unacceptable for canning.[12] If a delivery exceeds the damage threshold, processors reject all fruit in the delivery. Given our assumption that it takes k days for damaged fruit to fall from a tree, the cumulative proportion of fruit damaged within k days of harvest is counted against the damage threshold. We impose the following constraint in the model:

$$\sum_{t=T-k}^{T} \mathrm{d}_{it} \leq \bar{D}, \tag{6}$$

where $\bar{D}$ is the threshold level of damage set by processors prior to the growing season, which is exogenous to an individual producer.

11 This peculiar characteristic of the olive crop is borne out in the empirical data. After controlling for the alternate-bearing nature of olive trees and a time trend, there is no statistically significant relationship between the average quality of fruit produced and the total quantity of fruit produced, for any type of commercial canning olive.

12 Larval exit holes, which are necessarily highly correlated with lagged stings, are also observable.

Table 3. Simulation model indices and parameters

Index/parameter	Description	Value(s)
$i = 1, \ldots, 5$	Representative growers (by cultivar and region)	SV-SSV, MS-SSV, MZ-SSV, MZ-NSV, MZ-SJV
$t = 1, \ldots, 318$	Day of growing season	1 February to 15 December
$g = \mathrm{I, II}$	Olive group	Group I: SV, Group II: MZ, MS
r	Daily interest rate	1.07×10^{-4}
H	Cost of harvest	USD 3,336/ha
c	Cost of insecticide application	USD 25/ha
$y_{it}^{\max}$	Yield in metric tons/ha	$-81.368 + 0.71t - 0.0013t^2$, before 20 October $-776.58 + 6.01t + 0.0115t^2$, after 20 October
k	Days between fruit damage and fruit drop	14
θ	Insecticide efficacy	99 per cent
$\bar{D}$	Maximum damage allowed by processors	1.0 per cent

Notes: SV, MS, and MZ denote Sevillano, Mission, and Manzanillo cultivars; SSV, NSV, and SJV denote the Southern and Northern Sacramento Valley and the San Joaquin Valley. Representative growers and first day of growing season based on field data collected by collaborating entomologists. Harvest and insecticide application costs based on O'Connell *et al*. (2005) and Krueger *et al*. (2004). Insecticide efficacy based on personal communication with Frank G. Zalom (Department of Entomology, University of California, Davis). Interest rate based on annual rate of 4 per cent, which is similar to that used by Marsh, Huffaker and Long (2000), Livingston, Carlson and Fackler (2004), and Qiao *et al*. (2009). Maximum damage threshold: though processors in California have asserted a zero damage threshold, we assume that this translates practically into a limit of 1 per cent, a threshold consistent with European canning standards and one that accommodates imperfect detection.

3.2. Pest control strategies for individual growers

The indices and parameters described in the previous section and used in the analysis are summarised in Table 3. Average prices by size grade and cultivar group (Table 1) are used in the model. The five representative growers that we consider capture differences in the same cultivar across regions (MZ-SSV, MZ-NSV, and MZ-SJV) and across cultivars in the same region (MZ-SSV, SV-SSV, and MS-SSV).[13] For each grower, we first solve for the optimal harvest date with no pest damage. This scenario serves as the baseline prior to the infestation, which began in 1998. We then fix the harvest date at the baseline and introduce pest damage into the problem, solving the model for optimal insecticide applications. Finally, we allow for flexibility in harvest timing, solving for the combination of insecticide applications and harvest timing that maximises discounted profit over the growing season for each grower.

For a given harvest date, a grower chooses whether or not to apply insecticide each day of the growing season to maximise discounted growing season profit subject to equations (2)–(6). This is a standard finite-horizon dynamic

13 These acronyms are defined in Table 3.

optimisation problem with a fixed terminal period. Numerically, we use dynamic programming to solve the mixed-integer optimisation problem with the General Algebraic Modeling System (GAMS) software (Brooke *et al*., 2012). For a single harvest date, the objective function is linear and the constraint set is convex and non-empty, which ensures that a unique global optimum describing day-by-day insecticide use exists.[14] Introducing flexible harvest timing changes the problem slightly: a grower chooses the combination of harvest date and day-by-day insecticide applications that maximises growing-season profit. The grower's problem becomes a finite-horizon dynamic programming problem with a free terminal period. Numerically, we solve this problem in two steps. First, we solve for the optimal insecticide use schedule for every potential harvest date in a growing season. This yields a curve that defines the maximum profit a grower can earn as a function of the harvest date. We then choose the harvest date (and associated optimal insecticide use schedule) that maximises profit for each grower.[15]

Table 4 presents the baseline solution with no pest infestation. For all grower types save one, the optimal harvest date with no infestation is 20 October, the day on which yield peaks. For MS-SSV, it is beneficial to wait to harvest until 31 October, sacrificing some yield to allow fruit to grow larger and jump from the petite to the small size class for cultivars in Group II. After incorporating infestation, we find that the timing and level of damage differ substantially across growers. For the largest fruit (SV-SSV), the first infestation occurs on 8 July. For other fruit in the same region (MZ-SSV and MS-SSV), infestation does not occur until 9 August or 6 September. Baseline damage also differs substantially across cultivars: 95 per cent of SV-SSV, 60 per cent of MZ-SSV, and 28 per cent of MS-SSV olives are damaged by harvest. There is also variability across the same cultivar in different regions: MZ-NSV fruit become infested on 15 August, and exhibit baseline damage of 100 per cent and MZ-SJV fruit become infested on 24 August and exhibit baseline damage of 43 per cent. These levels are consistent with field observations.[16]

Table 4 details the model results with pest damage and fixed harvest timing. These results illustrate considerable differences in optimal treatment among

14 Although price depends on fruit size, the objective function is linear because fruit size does not depend on insecticide applications. This specification follows from the biological fact that damage does not negatively impact olive size and from the lack of correlation between olive size and yield.

15 We treat the harvest date as a parameter, looping the GAMS 'solve' statement over all feasible harvest dates and manually searching for the optimum, though the terminal date can be programmed as an endogenous variable, as outlined by McCarl and Spreen (1997). A copy of the programming code is available upon request.

16 Validation is based on an unpublished data set from the 2004 growing season, collected by Hannah J. Burrack (Department of Entomology, North Carolina State University) and Frank G. Zalom (Department of Entomology, University of California, Davis). Across regions, uncontrolled infestation rates range from 18–50 per cent for MZ, 80–95 per cent for SV, and 3–7 per cent for small oil cultivars. MS fruit fall between small oil cultivars and MZ in size and damage. Growers in the NSV have suffered most from the infestation; instances of orchard abandonment due to infestation have been reported there. In contrast, SJV growers have suffered relatively little from the infestation.

Table 4. Model results by representative grower with price menu exogenous

Representative grower	SV-SSV	MS-SSV	MZ-SSV	MZ-NSV	MZ-SJV
Baseline, no infestation					
Harvest date	20 October	31 October	20 October	20 October	20 October
Size (mm^3)	7,342	2,623	3,205	2,215	3,547
Yield (metric tons/ha)	11.20	9.84	11.20	11.20	11.20
Price (USD/metric ton)	911.47	576.92	1,115.38	421.24	1,133.70
Profit (USD/ha)	6,718.09	2,296.23	8,946.41	1,360.94	9,146.60
Fixed harvest date, with infestation					
Harvest date	20 October	31 October	20 October	20 October	20 October
GF-120 applied (l/ha)	17.50	7.68	11.96	10.54	9.11
Damage (per cent)	0.93	0.86	0.93	0.96	1.00
Size (mm^3)	7,342	2,623	3,205	2,215	3,547
Yield (metric tons/ha)	11.09	9.61	11.14	11.04	11.14
Price (USD/metric ton)	911.47	576.92	1,115.38	421.24	1,133.70
Profit (USD/ha)	4,256.33	1,132.54	7,265.50	−127.59	7,850.69
Flexible harvest date, with infestation					
Harvest date	9 October	31 October	11 October	8 October	13 October
GF-120 applied (l/ha)	15.89	7.68	10.71	8.93	8.04
Damage (per cent)	0.93	0.86	0.93	0.93	0.88
Size (mm^3)	7,143	2,623	3,060	2,004	3,421
Yield (metric tons/ha)	10.94	9.61	11.04	10.91	11.08
Price (USD/metric ton)	911.47	576.92	1,115.38	421.24	1,133.70
Profit (USD/ha)	4,342.71	1,132.54	7,329.49	36.27	7,932.48

Notes: SV, MS, and MZ denote Sevillano, Mission, and Manzanillo cultivars; SSV, NSV, and SJV denote the Southern and Northern Sacramento Valley and the San Joaquin Valley. Damage, size, yield, and price are values observed at harvest.

growers. For example, SV-SSV has the largest fruit and exhibits infestation earliest. As a result, this grower begins insecticide use on 9 July and continues into October. With fixed harvest timing, this grower applies the insecticide over 98 treatment days. Based on a treatment interval of seven days and an application rate of 1.25 l/ha from the insecticide label (Dow AgroSciences, 2012), this amounts to 17.5 l/ha of GF-120 over the growing season. In contrast, MS-SSV, with the smallest fruit, does not begin insecticide use until 7 September, continuing into late October for 43 treatment days. This grower applies 7.68 l/ha of GF-120 over the season.

Table 4 also presents results with flexible harvest timing. In all cases but one, it is optimal to harvest earlier than before the infestation. The greatest change occurs for MZ-NSV, which shifts harvest timing forward by 12 days. SV-SSV, MZ-SSV, MZ-SJV also shift harvest timing forward by 11, 9, and 7 days. MS-SSV does not change harvest timing because doing so comes with a substantial reduction in price (from small to petite, Group II). The difference in profit between the scenario with fixed harvest timing and that with flexible harvest timing is the return to the cultural control. The results suggest an increase in profit ranging from USD 63.98 to USD

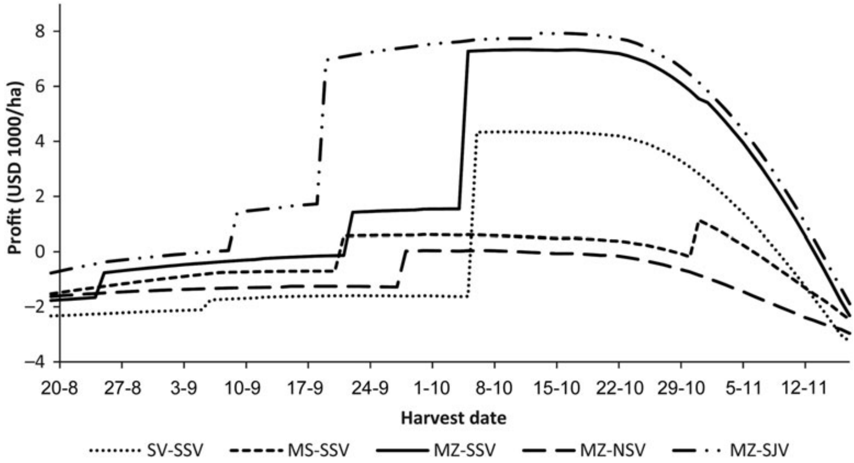

Fig. 2. Net present value of profit by harvest date and representative grower.
Notes: SV, MS, MZ denote Sevillano, Mission, and Manzanillo cultivars; SSV, NSV, and SJV denote the Southern and Northern Sacramento Valley, and the San Joaquin Valley.

163.86 per hectare. For MZ-NSV, the change in harvest timing increases profit from USD −127.59 to USD 36.27 per hectare. However, for all other growers, the change in profit due to changes in harvest timing is relatively small (0.88 to 2.03 per cent). Although the returns to changes in harvest timing are relatively small, they come with a substantial decrease in insecticide use. The largest decrease is for MZ-NSV, which reduces chemical applications by 15.3 per cent; MZ-SJV, MZ-SSV, and SV-SSV also decrease insecticide use by 10.4, 11.8, and 9.2 per cent. Across the industry, total GF-120 applications fall by 11.39 per cent with flexible harvest timing.

For each grower, the optimal date of harvest balances the revenue gain associated with a one-day delay in harvest with the costs of infestation. Figure 2 illustrates the net present value of profit by harvest date for each grower. Large changes in profit occur when a grower's crop reaches a size sufficient to jump from one size class to the next. During time intervals when a grower's fruit stay within a single size class, changes in profit are driven by insecticide applications, changes in yield, and discounting.

We test the sensitivity of the model to changes in several key parameters. With an increase in insecticide treatment cost, the cost associated with an incremental delay in harvest increases and a grower optimally harvests earlier. Growers' decisions over insecticide use and the choice of harvest date are insensitive to large changes in the discount rate. The effects of changes in weather on growers' decisions depend on how weather affects fruit size, baseline damage, and the price of a grower's crop. Unfavourable growing conditions imply smaller fruit, a lower price, and a decrease in the benefit associated with an incremental delay in harvest. However, smaller fruit also have a lower level of baseline damage, which decreases the cost associated with an incremental delay in harvest. Finally, changes in fruit size affect the timing of jumps in the price of a grower's crop. Growers will optimally delay harvest if doing so allows their fruit to increase a size class.[17] The combined influence of these three effects of weather is an empirical matter. We find that a 20 per cent decrease in growing degree-days throughout the season leads MZ-SSV and MZ-SJV to harvest 19 and 12 days later; SV-SSV and MS-SSV to harvest 1 and 3 days earlier; and MZ-NSV to harvest on the same date as that under average weather conditions.

4. Market effects of harvest-timing decisions

The analysis in the previous section illustrates heterogeneous pest management incentives among growers of different cultivars in different locations. Most growers reduce insecticide use by altering harvest timing, though to varying degrees depending on whether the incentive to delay harvest to increase fruit size outweighs the immediate within-season costs of infestation. In this section, we build on these results for individual growers to determine the collective effect of growers' choices on prices and the consequences of those price changes for welfare and pest management incentives.

Each growing season, a menu of prices by size grade and cultivar group (Table 1) are set via negotiation between the Olive Growers' Council of California, a grower collective, and industry processors. The price menu does not vary by date of delivery within a season because canners can store raw olives and process them throughout the year.[18] Prices are usually set in August, two months prior to typical harvest dates for all canning cultivars.[19] Although the price menu is established via negotiation, individual growers of olives are price-takers in the sense that they cannot influence the price menu for their group by manipulating their own output. However, as demonstrated in the previous section, a grower can choose into which size grade their crop falls by changing harvest timing.[20] Although the individual grower views the price menu as exogenous, widespread changes in the quantity or quality of fruit produced during a season may collectively drive a change in the price menu. This possibility is expressed in objective function (1), where the price that an

17 We also consider a smooth approximation to the stepped price function. The results of the model are qualitatively similar, which indicates that our conclusions are not driven solely by the discrete nature of the price function.

18 Upon delivery, processors place the raw fruit in large tubs of brine. Fruit can be stored this way for several months with no degradation in quality. Processors withdraw an amount of fruit to be processed each day, smoothing processing quantity over time. Therefore, processors' willingness to pay for specific sizes and cultivars depends on the quantity and quality of fruit delivered over the entire growing season.

19 Because we assume certainty in the model, the timing of price negotiations is irrelevant; the quantity and quality of fruit produced for the season is known by all growers and processors.

20 Goodhue, Mohapatra and Rausser (2010) demonstrate a similar result in the case of processing tomatoes. They show econometrically that growers increase their provision of quality attributes when faced with a price schedule for quality, relative to the case in which the price does not reflect an incentive for higher quality.

individual producer receives for fruit of size v is conditional on aggregate quantity (Q_g) and quality (V_g) produced within the relevant cultivar group.

In this section, we estimate how equilibrium prices change in response to the changes in quantity and quality that are driven by the insecticide use and harvest timing decisions of individual heterogeneous growers. We do so without making any assumptions about the bargaining process that takes place between the grower collective and processors. Rather, we use observed prices to estimate a reduced-form econometric model for each cultivar group that relates the equilibrium price observed by size grade to the aggregate quantity and quality of fruit produced within that group.[21] We then incorporate price endogeneity into the simulation model and re-simulate growers' pest management decisions. This enables us to determine how price changes affect growers' welfare and growers' choices of harvest timing and insecticide use.

4.1. Endogenous price model

We define the total quantity of fruit produced for a cultivar group as $Q_g = \sum_i a_{ig} y_{iT}$, where a_{ig} is land area in olive production by producer i in group g and y_{iT} is the yield at harvest. There are a number of potential descriptions of fruit quality. Following James and Alston (2002), we use weighted average size, i.e. $V_g = \sum_i w_{ig} v_{iT}$, where w_{ig} is the proportion of land area in production by producer i in group g, and v_{iT} is the size of fruit at harvest. We link representative growers with their industry weight in terms of land area from Table 2. In the baseline model scenario with no infestation, a total of 4,256 metric tons of olives are produced by Group I (SV-SSV). Those olives average 7,342 mm^3 in size at harvest (jumbo). Group II (MS-SSV, MZ-SSV, MZ-NSV, and MZ-SJV) produces 117,745 metric tons, with a weighted average size of 3,317 mm^3. Group II fruit range in average size from petite to large.[22]

Using data on the quantity of raw olives produced, the distribution of raw olive deliveries by size grade, and prices from 2000 to 2010, we estimate the reduced-form econometric model:

$$\ln p_{cgt} = \alpha_{cg} + \beta_{cg} \ln Q_{gt} + \gamma_{cg} \ln V_{gt} + \varepsilon_{cgt}, \tag{7}$$

where c indexes the size grade, g indexes the cultivar group, t indexes the year, and p is the observed price. The estimated slope coefficients are reported in Table 5.[23]

21 We assume that the total quantity and quality produced within each group do not affect price signals for the other group. Processing for the two groups of olives is very different, implying limited substitutability between the two, at least for processors.

22 Average sizes are consistent with data for the 2000–2010 growing seasons (California Olive Committee, 2010).

23 Price is determined prior to Q and V, and is set based on expectations.

Table 5. Estimated parameters for price by size and cultivar group

Group I			Group II		
Size class	ln Q	ln V	Size class	ln Q	ln V
Extra large limited	−0.1475	−1.0815	Sub-petite	−0.2952***	2.7968
Extra large canning	−0.0523	0.0160	Petite	0.3345***	4.2857*
Jumbo	−0.1232	−3.3479	Small	0.0334	5.0945**
Colossal	−0.0729	−2.1921	Medium	−0.1804	−2.9977
Super colossal	−0.0400	−1.8502	Large	−0.1408	−3.9053
			Extra large	−0.1413	−5.3469

Notes: The dependent variable is ln p_{cgt}, where p denotes price, and c, g, and t index size grade, cultivar group, and year. Q and V denote aggregate quantity and average quality of fruit. The number of observations is 55 for Group I, 66 for Group II.
*Statistical significance at the 10 per cent level.
**Statistical significance at the 5 per cent level.
***Statistical significance at the 1 per cent level.

Based on the model results for individual growers, we define how production and price change across scenarios. With pest infestation and fixed harvest timing, aggregate production falls to 4,216 and 116,962 metric tons for Groups I and II, relative to the pre-infestation baseline. Average size is unchanged. With flexible harvest timing, Group I produces 4,157 metric tons and Group II produces 116,101 metric tons, a decrease of 1.40 and 0.74 per cent relative to the scenario with fixed harvest timing. The weighted average size for Groups I and II with flexible harvest timing is 7,143 and 3,174 mm^3, a decrease of 2.72 and 4.31 per cent relative to the scenario with fixed harvest timing. These changes in production patterns are within the observed range of variation in our data set.

If processors anticipate the widespread changes in harvest timing that growers undertake in response to the infestation, and concomitant changes in the aggregate quantity and quality of fruit produced, prices for raw olives will change in response. In the case where price is endogenous, the results of Section 3.2 no longer represent an industry equilibrium. In this section, we solve for the industry equilibrium with endogenous prices. In equilibrium, the growers' profit-maximising choices of insecticide applications and harvest timing result in the aggregate quantity and quality that are associated with the equilibrium price menu. We maintain the assumption that agents operate under certainty, which implies that growers and processors anticipate changes in yield, quality, and prices for a growing season. We also assume that prices for Group I and Group II olives are determined separately. Fruit in the two groups differ physically and require separate processing technology, which limits their substitutability in processing. They also differ substantially in size, which limits substitutability in consumption.

We solve numerically for the price-endogenous equilibrium for each cultivar group as follows: we start with the changes in Q and V predicted by the price-exogenous model, estimate the corresponding change in price by size class, and re-solve each grower's harvest timing and insecticide use problem. The results of that simulation imply a second-round change in Q and V, which generates another change in price. We continue to iterate until there are no further changes in growers' behaviour or prices, which occurs after three iterations for Group I and four iterations for Group II.[24]

4.2. Results of the endogenous price model

Table 6 reports the results by grower when prices are endogenous. Overall, price endogeneity provides growers with an incentive to delay harvest timing relative to the case in which price is exogenous. This is most strikingly the case for MZ-SSV, which delays harvest by six days relative to the optimum with exogenous price. SV-SSV and MZ-SJV delay harvest by one or three days. In each case where harvest is delayed, the amount of GF-120 applied over the season increases, but never exceeds the case with a fixed harvest date. With exogenous prices, the model suggests that GF-120 use falls by 11.88 per cent across the industry due to changes in harvest timing. Accounting for price endogeneity, that change is smaller, amounting to 8.36 per cent.

Table 6 also highlights the welfare consequences of changes in price. The maximum potential loss from infestation is the difference in profit under the pre-infestation baseline and profit with infestation but no pest control, either cultural or chemical.[25] The use of chemical control reduces losses by 23–74 per cent. Adding flexibility in harvest timing reduces losses by up to an additional 11 per cent. Incorporating price endogeneity, however, increases the losses for some and reduces the losses for others, relative to the price exogenous case. The two growers harmed by the price change are MS-SSV and MZ-NSV, both in Group II. For MS-SSV, losses increase by USD 785.74 per hectare (67.5 per cent); for MZ-NSV, losses increase by USD 544.70 per hectare (41.1 per cent). The other two grower types in Group II benefit from the price change: For MZ-SSV, losses fall by 50 per cent; for MZ-SJV, the largest fruit in Group II, losses fall by 85 per cent. The grower in Group I, SV-SSV, also benefits from the price change, with a decrease in losses of 32 per cent.

Who gains and who loses from changing prices is dictated by the relative position of a grower's fruit in the group's size distribution. When changes in harvest timing reduce the average size of fruit across Group II, prices for small olives decrease, while prices for large olives increase. The endogenous price change thus increases the reward associated with size and decreases incentives to substitute changes in harvest timing for insecticide applications.

24 This iterative solution method is simply a technique to achieve numerical convergence; it implies nothing about growers' and processors' behaviour.

25 In this case, none of the growers can satisfy constraint (6). We relax that constraint and calculate losses based on yield reductions from infestation. Failure to meet the damage constraint can result in rejection of the entire crop by processors, in which case these estimates are understated and the maximum loss from infestation is equal to profit in the pre-infestation baseline.

Table 6. Model results by representative grower with endogenous price menu

Representative grower	SV-SSV	MS-SSV	MZ-SSV	MZ-NSV	MZ-SJV
Flexible harvest date, with infestation					
Harvest date	10 October	31 October	17 October	8 October	16 October
GF-120 applied (l/ha)	16.07	7.32	11.43	8.93	8.39
Damage (per cent)	0.93	0.86	0.90	0.93	0.99
Size (mm^3)	7,172	2,623	3,155	2,004	3,480
Yield (metric tons/ha)	10.97	9.52	11.13	10.91	11.12
Price (USD/metric tons)	982.22	492.74	1,189.76	370.13	1,228.72
NPV (USD/ha)	5,099.88	346.80	8,137.00	−508.44	8,960.18
Summary of welfare changes (USD/ha)					
Maximum loss from infestation	8,809.55	1,509.17	6,508.02	4,440.46	4,599.05
Loss with chemical control, exogenous price	2,461.77	1,163.69	1,680.91	1,488.53	1,295.91
Loss with cultural and chemical control, exogenous price	2,375.39	1,163.69	1,616.93	1,324.67	1,214.12
Loss with cultural and chemical control, endogenous price	1,618.22	1,949.43	809.42	1,869.37	186.41

Note: SV, MS, and MZ denote Sevillano, Mission, and Manzanillo cultivars; SSV, NSV, and SJV denote the Southern and Northern Sacramento Valley and the San Joaquin Valley. Damage, size, yield, and price are values observed on the harvest date.

These gains and losses are particularly pronounced in the canning olive industry because the potential for growers to change the quality of their product is limited. For a perennial crop like olives, quality is dictated, to an extent, by location of production and cultivar. The choice of cultivar is one that was made when trees were planted, in many instances decades earlier. The implication is that an olive can only grow so large within the course of a season. The ability of growers to change cultivars is also limited because of the time required to bring immature olives to fruiting (eight years) and because of the long productive lifetime of an olive tree (forty years for commercial canning cultivars in California). Under these circumstances, crop biology constrains the ability of growers of small fruit to capture an increase in price premium for larger fruit.

5. Conclusion

In this analysis, we present a model of individual pest management decisions on two margins. We demonstrate that growers of canning olives in California face heterogeneous control incentives. In particular, differences in incentives to undertake cultural control arise from the nature of pest–host biology and from the industry's price structure. Larger fruit are more susceptible to damage by the olive fruit fly, but they also receive a price reward from the processing market. The tension between these opposing effects and their relative strength determines the optimal date of harvest for an individual grower.

Because cultural control alters the quantity and quality of fruit produced across the industry, the harvest timing decisions of individual growers collectively affect the price signals that they each face. The key issue highlighted here is that aggregate changes in production due to cultural control alter the reward for an improvement in quality. The effect of this price endogeneity is to reduce the incentive for growers to use cultural control, increasing reliance on chemical control. This result suggests that, for crops other than olives, non-chemical control methods that are neutral with respect to those dimensions of quality that the market values may stand a greater chance of adoption than those that are not quality-neutral. Furthermore, the change in the price function resulting from changes in aggregate production redistributes welfare among growers. Those producers who gain the most are those well-situated growers who already produce the highest quality fruit. Growers of lower quality fruit stand to lose because they are limited by crop biology in their ability to respond to changing price signals for quality.

Two main policy implications arise from this analysis. First, any policy that alters the tradeoff between productivity and pest damage may alter the incentives that growers face to engage in cultural versus chemical control. Examples might include policies that directly regulate pesticide use in order to protect environmental quality or human health, or agricultural policies such as grades and standards. This analysis underscores that it is important to consider the impacts of these policies not just on the quantity of a crop produced, but also on its quality. Second, the market feedback effects that arise in the presence of grower heterogeneity likewise affect decisions about the use of insecticides. By influencing pest control decisions, these feedback effects carry implications for the production of externalities, including the effects of chemical use on human health, environmental quality, and agricultural productivity in the future.

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