The Role of Harvest Timing in Pest Management: Grower Response to Infestation by the California Olive Fruit Fly

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Studies of pest management in agricultural production focus on determining the optimal use of pest control inputs while treating harvest dates as inflexible. Our analysis adds to the agricultural pest management literature by modeling the choice of harvest date as another tool that producers may use to mitigate damage from a pest. In this paper, we formulate a stochastic intra-seasonal model of joint harvest and damage control input decisions at the level of the individual grower. We frame the analysis within the empirical context of the olive fruit fly infestation in California.

As well as expanding the set of feasible management options available to a grower, the choice of when and whether to harvest may alter the character of interior pest treatment optima. Specifically, growers may alter their harvest date to reduce the cost of pest control input applications throughout the season. In the extreme, by altering harvest timing, the grower may avoid application of pest control treatments altogether. Alternatively, a grower may abandon production mid-season, ceasing treatments from that moment, if pest damage escalates to such a level that continued production yields expected losses that exceed the costs of production to date.

Significant potential exists for harvest timing to affect growers' management of pest damage in our example. In general, the olive crop in California is mature well in advance of traditional harvest dates. However, even after fruit attains maturity, it increases in size, a characteristic that is rewarded with price premiums from processors. The tradeoff for a grower against a higher price for larger fruit is that olives become more susceptible to fly damage as they increase in size. Anecdotally, California olive growers have sometimes responded to the fly infestation by altering harvest timing to reduce insecticide use or to avoid losses due to high damage rates late in the growing season.

Fly damage affects both yield and fruit quality. Damage to olives by the fly reduces yield (in tons per acre) over the growing season via premature fruit drop. It is important at this point to define what we mean by fruit quality. One component of fruit quality is olive size, which determines the price received by a grower on delivery to a processor. Fly damage does not directly affect the equation of motion governing changes in fruit size. The second quality component is the percentage of fruit that show evidence of fly infestation. The fly stings olives to oviposit, leaving visible holes which ruin the fruit's aesthetic and preclude them from canning. Subsequent larval development inside an olive destroys the fruit's sensory characteristics by introducing an avenue for fungal and bacterial infections. This type of advanced infestation prohibits olives from oil processing as well. Both canning and oil olive processors enforce quality standards at the processing gate, rejecting deliveries with a damage rate exceeding a set threshold.

The model of intra-seasonal pest management decisions that we present incorporates detailed pest-host biological relationships into a stochastic optimization framework. We focus our attention on yield loss due to fly infestation. In particular, we evaluate the tradeoff involved in delaying harvest to allow fruit to increase in size with the decrease in yield associated with extending production into periods of peak infestation late in the growing season. We solve the problem numerically in order to determine the combination of treatment strategy and harvest date that maximizes returns for a representative producer of several olive cultivars across the state's producing regions. We conclude by comparing optimal management practices when harvest timing is fixed versus when it is flexible.

Relevant Literature

Pest control inputs are one in a larger class of inputs that are designed to mitigate damages or losses realized during production. Producer decisions regarding the use of damage control inputs differ from decisions regarding "positive" inputs. The latter affect productive yield directly. In contrast, damage control inputs influence output indirectly by reducing negative deviations from the yield level determined by positive inputs (Feder and Regev 1975; Lichtenberg and Zilberman 1986).

Lichtenberg and Zilberman (1986) demonstrate that the way in which damage control inputs enter a production function alters predicted behavior by a profit-maximizing producer. They express production (*Q*) as a function of positive inputs (*Z*) and a damage abatement function (*G*(•)) that depends on pest control inputs (*X*), i.e. $Q = F\left[Z, G(X)\right]$. They show that treating *X* as a positive input, or assuming a production function of the form $Q = F\left[Z, X\right]$, leads to overestimates of the marginal productivity of *X* in an econometric analysis. They also demonstrate that incorporating *X* indirectly via a damage abatement function is particularly important in the presence of pesticide resistance, which generates temporal externalities across growing seasons.[1] When pest resistance to *X* increases over time, treating *X* as a positive input (assuming the standard properties for a neoclassical production function) yields the conclusion that use of the input will decline over time as its marginal productivity decreases. Incorporating *X* in the production function via *G*(•) yields exactly the opposite prediction, which corresponds to observed producer behavior. In short, a producer first chooses the optimal level of

[1] Lichtenberg and Zilberman (1986) demonstrate that this result holds under the assumption that pesticide resistance dynamics are governed by the aggregate use of the pest control input, i.e. an individual producer views his use of *X* as having a negligible impact on regional resistance dynamics. In this case, an individual grower's problem can be characterized as one of sequential myopic decision-making.

abatement, then the level of *X* required to obtain that goal. Thus, as *X* declines in efficacy, a grower will tend to increase their use of the damage control input over time.

The framework specified by Lichtenberg and Zilberman provides the foundation for two subsequent analyses that highlight additional points to consider when modeling pest control input decisions. Babcock, Lichtenberg, and Zilberman (1992) incorporate the quality effects of pest control inputs in addition to yield quantity impacts. They demonstrate that, when a pest control input affects yield and product quality, failing to account for quality understates the optimal level of pest control input use. Saha, Shumway, and Havenner (1997) allow damage abatement to depend on both *X* and elements of *Z,* i.e. $Q = F[Z, G(X, z)]$, where $z \subseteq Z$.[2] They consider the case in which fertilizer applications enhance pest survival, reducing the efficacy of *X* in damage abatement. In their model, the optimal level of fertilizer takes into account the direct marginal benefit of fertilizer on production as well as its marginal cost in terms of requiring increased *X* to attain the optimal level of damage abatement.[3]

These three analyses do not explicitly define a pest damage function. Rather, they implicitly include the baseline level of damage in the production function (as output

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[2] Lichtenberg and Zilberman consider a similar formulation in their definition of a production function in the face of increasing pesticide resistance (*R*): $Q = F[Z, G(X, R)]$. However, *R* enters only into the abatement function. It does not affect output both directly and indirectly as in Saha, Shumway, and Havenner's specification.

[3] Assume the existence of a unique interior maximum (i.e. convexity in the production function) and differentiability of the production and abatement functions. For a producer operating in a perfectly competitive environment, with single positive input *z* and damage abatement input *X*, with exogenous unit prices *r* and *w*, respectively, the profit-maximizing problem can be written as

$$\max_{X,z} \Pi = pF[z, G(X, z)] - rz - wX.$$

The first-order conditions for profit maximization imply that

$$\frac{\partial F}{\partial G}\frac{\partial G}{\partial X} = w \text{ and } \frac{\partial F}{\partial z} + \frac{\partial F}{\partial G}\frac{\partial G}{\partial z} = r$$

where $\frac{\partial F}{\partial G} > 0$, $\frac{\partial G}{\partial X} > 0$, $\frac{\partial F}{\partial z} > 0$, and $\frac{\partial G}{\partial z} < 0$.

when abatement equals zero). The pest management literature most often models pest damage as a function of the pest population (see, for example, Feder and Regev 1975; Regev, Gutierrez, and Feder 1976; Moffit, Hall, and Osteen 1984; Pannell 1991; and Deen et al. 1993). It follows from this conceptualization of damage that abatement takes the form of a "kill" function, i.e. the proportion of the pest population eliminated with the use of one or more pest control inputs.

Several studies highlight cases in which population-based damage and abatement functions may be incorrect. McKee et al. (2009) identify the importance of distinguishing the age distribution of the pest population when defining a damage relationship. The authors also define damage as a function of pest activity, which depends on both the pest population and the amount of time spent within biological development thresholds. Marsh, Huffaker, and Long (2000) consider an example in which a pest transmits a virus to a host and the level of viral infection determines crop quality and quantity damage. Their empirical analysis indicates that the optimal timing of pest control applications coincides with periods when an insect pest is most efficient at transmitting a virus. This timing need not coincide with periods in which the pest population is largest. Christiaans, Eichner, and Pethig (2007) derive a crop production function based on micro-level constrained optimizing behavior by a pest and a host. Their approach allows simultaneity in host susceptibility and pest population levels. In so doing, they find that an optimal management approach may include enhancing crop resilience to infestation, reducing pest populations, or by altering some input that accomplishes both ends.

The analyses discussed in this section, taken together, highlight three key quantitative relationships to define in an analysis of pest control incentives. The first key relationship defines the damage process. One should consider the mechanics of the damage process, such as whether the pest population directly inflicts damage (and what portion of the population damages the host) and whether the level of damage at any point in time depends on other factors, such as the susceptibility of the host or temperatures. The second defines yield as a function of positive inputs. As in Babcock, Lichtenberg, and Zilberman (1992), the specification of potential yield should include a quality dimension, in addition to quantity considerations, when quality plays a role in determining growers' returns. The third component is the damage abatement function. In general, this function depends on inputs specifically designed to mitigate damage (such as insecticide applications) and inputs that jointly affect yield and abatement.[4]

We are not aware of any literature that examines joint harvest and pest control treatment decisions directly. However, the harvest timing decision considered in this analysis fits well within the framework described by Saha, Shumway, and Havenner (1997). The olive harvest date plays both positive and damage abatement roles in the production function. Absent fly infestation, the optimal harvest date maximizes fruit yield quantity and quality by balancing increases in fruit volume with the risk of an over-ripe crop, premature fruit drop, and freeze damage (Sibbett and Ferguson 2005). However, harvest timing is now another means of limiting olive fruit fly damage. The optimal date of harvest will balance the marginal losses from increasing damage with the gains in revenue from fruit growth associated with a delay in harvest. In this paper, *X* represents insecticide applications and *Z* includes harvest timing along with other productive inputs.

[4] Saha, Shumway, and Havenner (1997) point out that their damage function specification, $Q = F[Z, G(X, z)]$ involves assumptions about the separability of inputs. This specification assumes that the marginal rate of substitution among pairs of inputs included in *X* is independent of elements of *Z* not included in *z*. The authors recommend pre-testing for separability if possible. We discuss this issue in the context of our empirical application in the modeling subsection.

The Olive Fruit Fly in California

This analysis focuses on an empirical application to the olive fruit fly (*Bactrocera oleae*), an invasive species that became established in all California olive-producing regions between 1998 and 2004. The fly does not harm the future productivity of an olive tree, it damages only olive fruit. The fly is monophagous – olives are its only reproductive medium – and it does not inflict damage on any other flora.[5] However, damages to California olive producers can be severe. Left uncontrolled, the majority of olive cultivars grown in California sustain 80 to 100 percent damage over the course of a growing season. The domestic olive industry is particularly vulnerable to infestation from an economic standpoint. Over 98 percent of the olives grown in California are processed into canned table olives. Because canned fruit remains intact visible fly damage renders olives unacceptable for any type of canning. Table processors currently enforce a zero-damage threshold for raw olives.

The mechanism of damage by the olive fruit fly is reproduction. The fly damages fruit first when it oviposits (stings and lays an egg in the fruit's pulp, leaving a visible puncture), and later as the egg develops into a larva which feeds on the interior of the fruit. The size of olive fruit also plays a critical role in the damage process, as female flies prefer larger olives (Cobourn et al. 2008). Thus, the female fly population influences the amount of ovipositional activity, but the most advanced infestation is a function of immature fly development after oviposition.

[5] It remains to be seen whether the fly might jump to another host. However, the olive fly has a long history in Mediterranean olive-producing regions, possible dating as far back as the third century B.C. (Vossen, Varela, and Devarenne (2005), during which it has not infested any host outside of olive tree species included in the family *Olea europaea*.

Prior to the arrival of the olive fruit fly in California, there were no registered pesticides for olives that could be used to combat fly infestation. Today, two insecticides, GF-120 Naturalyte Bait (Dow AgroSciences LLC) and Surround WP (Engelhard Corporation), are registered with the California Department of Pesticide Regulation (CDPR) to mitigate fruit fly damage. At present, the fly has no natural enemies in California. There are a number of other control mechanisms for olive fruit fly, including cultivation and trapping (Johnson et al. 2006). However, none of these reduce damage to a level sufficiently low for either canning or oil processing.

Surround WP works by coating the fruit with a layer of kaolin clay. After harvest, fruit treated with Surround require intensive washing prior to processing, and the treatment's effect on olive quality is uncertain. The efficacy of Surround hinges on whether all fruit are completely covered by the clay mixture. Surround is therefore both costly and time-consuming to use. Surround is not used widely in commercial olive orchards in California at present.

Table 1. Percent olive fruit fly damage by treatment, 2004

Treatment	Damage (%)
Kaolin clay	2.18 [a]
GF-120	3.88 [a]
Attract and Kill	14.53
Yellow Sticky Trap	30.78 [b]
Olipe Trap (plain)	32.58 [b]
McPhail Trap	33.95 [b]
Olipe Trap (combination)	45.78 [c]
Olipe Trap (spiroketal)	59.75 [c]
Control (untreated)	87.62

a,b,c: data followed by the same letter is not significantly different at the five percent level.
Source: Vossen and Devarenne, 2007.

GF-120 is a Spinosad bait formulation that has been used successfully to combat a number of tropical and temperate fruit flies in the family Tephritidae.[6] Spinosad is a bait that attacks a pest's nervous system upon ingestion and leads to death. Several studies have demonstrated, in the context of Tephritids other than the olive fruit fly, that Spinosad is not harmful to natural parasitoids or to beneficial insects. Therefore, the treatment does not encourage secondary pest outbreaks (Stark, Vargas, and Miller 2004; Thomas and Mangan 2005). Moreover, Spinosad-based control formulations pose relatively little risk to human and environmental health (Revis, Miller, and Vargas 2004).

GF-120 is the most widely used insecticide to control olive fruit fly damage in California. The University of California Integrated Pest Management (IPM) program recommends that producers dilute the bait at a ratio of one part insecticide to 1.5 parts water. The dilution is applied from the ground with a spray gun mounted on an all-terrain vehicle, with the goal of coating the underside of the plant's leaves. Doing so prevents droplets from drying out in the sun and extends the number of days over which the bait is effective. The spinosad mixture need not be sprayed on every tree within a grove at once because flies can detect the bait from several yards away (Dow AgroSciences LLC 2006). The recommended practice is to spray the spinosad-water mixture on every other row of trees each week, from the first date of fruit susceptibility through harvest. The CDPR prohibits producers from applying GF-120 more often than every five days or more than 19 times per tree in one season (CDPR 2005).

[6] Spinosad bait formulations have been used to control the Caribbean fruit fly (*Anastrepha suspensa*), Mexican fruit fly (*Anastrepha ludens*), the Melon fly (*Bactrocera cucurbitae*), the Mediterranean fruit fly (*Ceratitis capitata*), the apple maggot fly (*Rhagoletis pomonella*), and the blueberry maggot (*Rhagoletis mendax*; Pelz et al. 2005; Prokopy et al. 2003; Stark, Vargas, and Miller 2004).

GF-120 treatments have been shown to reduce damage rates by the olive fruit fly from their uncontrolled level by 95.5 percent (table 1). However, even when used per IPM recommendations, the efficacy of the bait diminishes rapidly after application. Revis, Miller, and Vargas (2004) find that melon flies are significantly more attracted to fresh bait than that bait spray applied as little as 24 hours earlier. Precipitation events are even more detrimental to spinosad bait efficacy, reducing fly mortality rates by up to 50 percent (*ibid*.).[7] Taken in combination with the five-day minimum wait between sprays, the diminishing power of the bait makes olive groves particularly vulnerable to pest re-entry. The olive fruit fly is a highly mobile pest, traveling up to 6.5 kilometers without rest to find a host (F.G. Zalom, personal communication, 2008). As a result, the efficacy of GF-120 suffers when there are untreated olive trees outside of the treated grove but within the pest's range of mobility. Depending on weather factors and the proximity of untreated trees, which serve as a pest reservoir or refuge, GF-120 may suppress damage rates for as little as four or as many as 14 days after application (Prokopy et al. 2003; Mangan, Moreno, and Thompson 2006).

The Producer-level Optimal Control Model

In this section, we develop a modeling approach to examine the intra-seasonal pest treatment and harvest timing incentives facing California growers producing a variety of olive cultivars used in the canning and/or oil processing sectors under uncertainty. We consider a representative producer for each of fifteen location-cultivar combinations.[8]

[7] However, the authors find that temperature and relative humidity do not affect fly mortality rates.

[8] The producing area-cultivar combinations are Sierra Foothills: Region I/Leccino; Northern Sacramento Valley: Region II/Manzanillo, Region II-Mission; Southern Coastal Sacramento Valley: Region III/Arbequina, Region III/Frantoio, Region III/Koroneiki, Region III/Leccino, Region III/Manzanillo, Region III/Mission, Region III/Sevillano; Northern Coast: Region IV/Mission; San Joaquin Valley: Region

These location-cultivar combinations span the full range of commercial production regions and include a heavy representation of Manzanillo and Mission olives, the two most popular cultivars grown in California.[9]

The Optimization Model

The olive fruit fly is a highly mobile pest. Additionally, it is well-known in the olive industry that an individual producer's treatment decisions have a negligible impact on fly population dynamics. Rather, the pest population over time depends on treatment by all producers within a region (as defined by the extent of pest mobility and the growers' time horizon). Regev, Gutierrez, and Feder (1976) explain that these conditions uniquely generate the potential for stock externalities. The immediate implication is that from the point of view of an individual producer (unless that producer is sufficiently large relative to the producing region) pest population dynamics are exogenous.[10] If so, each producing agent behaves myopically, sequentially optimizing in each time period by choosing the level of pest control inputs (Feder and Regev 1975).[11] Thus, a successive static optimization approach for pest control input decisions is appropriate for our empirical application.[12]

V/Manzanillo; Southern Coast: Region VI/Mission; and Southern Inland Sacramento Valley: Region VII/Manzanillo, Region VII/Mission. Manzanillo, Mission, and Sevillano cultivars can be used for either canning or oil production (though traditionally for the former). Arbequina, Frantoio, Koroneiki, and Leccino are cultivars grown specifically for oil.

[9] Glenn and Tehama Counties, which together account for 11 and 15 percent of the total value of olive production in California, formed producer-funded Pest Management Districts (PMDs) early in the course of the olive fruit fly infestation. The PMDs enforce uniform spraying standards across orchards in both counties, and remove untreated ornamental trees.

[10] A parallel is that of perfect competition, in which no individual producer affects the price of their product, but the actions of all producers taken in aggregate affect price.

[11] A social planner for the region would, in contrast, consider pest population dynamics when determining optimal pest control practices.

[12] This approach is appropriate only if the representative producers considered are small relative to the size of a producing region. On average, oil olive growers cultivate 14 acres and table olive growers hold 32 acres, out of a total of about 5,000 oil acres and 25,000 table olive acres (National Agricultural Statistics

We formulate the producer-level pest control model with endogenous harvest in discrete time. The model's state variables include average olive size in each period (v_t) and the maximum proportion of the crop damaged by the fly in time period t (nd_t). The grower chooses whether to apply a chemical insecticide at a fixed rate in period t (u_t). We focus on treatment timing alone, treating the rate of application as fixed, as in Swinton and King (1994). We do so for two reasons. First, growers are constrained by liability issues to apply insecticide treatments per the manufacturer's recommendation on the product label. Second, because the olive fruit fly and its chemical control products are new to California, little is known about differences in efficacy for variable application rates. Under these circumstances, it is reasonable to assume that producers apply the insecticide at the recommended dilution.

When harvest is endogenous, the grower chooses the terminal period T that maximizes expected profit for the season.[13] We assume that the grower operates a mature orchard; we do not model decisions concerning the planting date. The optimal harvest timing decision takes into account expected changes in yield over the growing season. Expected yield changes depend on the use of pest control inputs. The grower's objective in terms of harvest timing is

(1) $$\max_T E(\Pi_T) = E\left[P(v_T) * y_T - H(y_T) - \sum_{i=1}^{T-1}(S * u_i + c_i) \right].$$

2007). Oil olive acres are more spatially dispersed than table olive acres, which are concentrated in the Sacramento and San Joaquin Valleys. Due to the spatial concentration of the majority of olive acres this assumption seems reasonable.

[13] Because the harvest window is so short, on the order of a couple of months, the discount rate is negligible. Therefore, the grower's objective is to maximize expected profit rather than expected net present value. For modeling simplicity, we assume that harvest can be implemented and completed in a single period. In reality, harvest takes anywhere up to four weeks to complete. One could view the choice of harvest date here as the median date in the optimal harvest period.

$P(v_T)$ is the per-unit value of the crop at harvest which depends on contemporaneous average olive size (v_T). Revenue at harvest is a function of fruit size and yield (y_T). Harvest costs are denoted H and depend on yield. The final term on the right-hand-side of **(1)** is the sum of per-period variable costs prior to period t. These include the costs of insecticide treatments, where S is the cost of a single application, and u_t is a binary variable indicating whether the insecticide was applied in t. Other variables costs are included in c.

Equation **(1)** implicitly defines the optimal terminal period T^* as a function of yield, which depends on fly damage and insecticide treatments, which in turn affect the damage rate over the course of the growing season. T^* is on the order of 228 to 304, measured in days from the beginning of the growing season and corresponding to September 15 to December 1. Damage control efforts affect yield in **(1)** as follows. In the absence of fly infestation, let $y_0 = py_0$, and $y_{t+1} = y_t + \Delta py_{t,t+1} = y_t + \left(py_{t+1} - py_t\right)$. Yield in the absence of pest damage follows an equation of motion that depends on the change in average pre-infestation yield (py) in each period. This equation of motion takes into account yield loss due to factors other than pest damage in an average year.[14]

Yield in the presence of pest damages depends on py and the amount of fly damage in each period, which is denoted d_t and is observed at the beginning of t. We express the damage rate as a proportion of the crop remaining on an olive tree. Therefore, the change in damage rate on day t is the difference in observed damage between period t

[14] The main factors that reduce yield from its potential include extreme weather events and non-optimal management (irrigation, pruning, thinning, or fertilization). We assume that producers manage their orchards optimally so that we can isolate the effect of pest control inputs as in Talpaz et al. (1978). We also assume that if extreme weather events occur and affect yield, they do not also affect the optimal timing of pesticide applications.

and t+1. Yield with fly infestation is $y_{t+1} = (y_t + \Delta py_{t,t+1}) * (1 - \Delta d_{t,t+1})$. Thus yield today is a function of pest damage in t = 1,…,t-1.

As discussed in the introduction, fly damage translates into yield loss because damaged fruit tend to drop from the tree prematurely. Olive fruit set at the beginning of the season determines total potential yield for a tree. In our model, the amount of yield lost in period t is related to fruit damage in previous periods. Unfortunately, there are no data available on the amount or timing of fruit drop due to fly infestation. The maximum amount of fruit that may drop prematurely is equal to the total proportion of the crop damaged up to the current time period. We specify yield loss as yield in t-1 less the proportion damaged between t-1 and t, thereby placing an upper bound on yield loss.[15]

A producer's choice to treat in period t affects the change in damage between t and t+1. Specifically, if no insecticide is applied ($u_t = 0$), the incremental change in damage between t and t+1 is given by $\Delta d_{t,t+1} = nd_{t+1} - nd_t$. We assume that insecticide applications reduce the damage in any period by a proportional amount equal to $\delta \in [0,1]$.[16] The incremental change in damage between t and t+1 if an insecticide is applied ($u_t = 1$), is $\Delta d_{t,t+1} = \delta * (nd_{t+1} - nd_t)$, $\forall t \in [0,T]$. As a starting point, we assume that the bait remains effective for a certain period of time after an insecticide application and that the proportion of damage abated over that period is constant. In practice, the length of efficacy depends on weather during the intervening period and the proximity of

[15] Alternatively, this is the yield loss if a producer were to separate damaged and undamaged fruit at harvest and deliver only undamaged fruit to the processor. To explicitly consider this option, we would simply extend the model to include sorting costs as a function of the proportion of fruit damaged at harvest.
[16] Studies in the entomological literature uniformly measure the efficacy of spinosad as a proportional reduction in pest damages (Mangan, Moreno, and Thompson 2006).

the closest untreated olive tree. We later extend the model to consider the case where damage abatement potential varies with time after application.

In periods prior to harvest, the grower decides whether or not to apply an insecticide to suppress pest damage. The grower's objective is to maximize the current period's contribution to profit at harvest:

(2) $$\max_{u_t} E(\Delta\Pi_{t,t+1}) = E[P(v_T)*(y_{t+1}-y_t) - H(y_{t+1}-y_t) - S*u_t].$$

The decision rule is to apply the insecticide if $E(\Delta\Pi_t \mid u_t = 1) > E(\Delta\Pi \mid u_t = 0)$. The maximization above defines implicitly the optimal treatment decision in period t, u_t*, which depends on the price expectation at harvest (and therefore on T* which affects expected damage).

Two biological relationships describe the equations of motion for the system. The uncontrolled damage rate and average olive volume at t are outside of the control of the individual producer and are given by:

(3) $$nd_{t+1} - nd_t = f_d(v_t, \mathbf{X}_t, \varepsilon_t), \quad t = 1,...,T \text{ , and}$$

(4) $$v_{t+1} - v_t = f_v(\mathbf{Z}_t, \nu_t), \quad t = 1,...,T \text{ .}$$

Equations **(3)** and **(4)** are as in Cobourn et al. (2008). **Z** includes variables describing weather and management practices. **X** includes olive size as well as weather and management variables. The ε and ν are stochastic error terms that capture uncertainty in the uncontrolled damage and olive volume trajectories.

In any pest management problem there may be multiple sources of uncertainty. As discussed by Pannell (1991), stochastic variation may characterize pest population densities, pesticide efficacy, the actual amount of pesticide applied, maximum potential yield in the absence of pest damage, pest damage rates, realized yield, and output price.

While a large number of analyses consider a single source of stochasticity, few model interacting stochasticity from multiple sources. Deen et al. (1993) consider uncertainty in both a pest's spatial distribution and in maximum potential yield. However, the authors do not comment on the implications of treating multiple sources of uncertainty separately or jointly. Saha, Shumway, and Havenner (1997) consider stochasticity in yield and a damage abatement function explicitly. They find significantly different estimates of pesticide productivity when they include a random error term in both functions.

We choose to limit our attention in this analysis to random variation in olive size and the uncontrolled damage rate. Some of this variation is driven by weather, which also impacts average pre-infestation yield (*py*). However, Cobourn et al. 2008 discuss substantial remaining uncertainty regarding olive size, olive fruit fly damage rates, and the appropriate damage function specification. The authors find evidence of correlation between stochastic variation in olive size and infestation rates. These sources of uncertainty likely have important ramifications for intra-seasonal management of the olive fruit fly in California. Therefore, we explicitly model correlated uncertainty in **(3)** and **(4)**.

Model Implementation

For the numerical programming model, we specify t as day of the growing season. The first day of the season is February 1, which is the biofix used to estimate equations **(3)** and **(4)** in Cobourn et al. (2008). The season ends on December 15 (t = 318), two weeks after the latest traditional harvest date for the region-cultivar pairings considered. To solve the treatment problem with exogenous harvest, we set T equal to the historically-optimal average harvest date and solve the period-by-period pest control input problem.

Table 4 lists historically-optimal harvest dates by producing region and cultivar (Sibbett and Ferguson 2005). For the joint harvest-treatment problem, we initialize the model with the pre-infestation average optimal T and iterate over **(2)** and **(1)** until convergence.

The olive volume and uncontrolled damage trajectories are based on the damage specification, estimation methodology, and dataset described by Cobourn et al.[17] The equations are as follows:

(5)
$$\begin{aligned} nd_{jt} = &-1.16945 + \left(0.52*10^{-3}\right)* v_{jt} - \left(0.85*10^{-4}\right)* v_{jt} * LT_t - \left(0.57*10^{-2}\right)* AD_{jt} \\ &+ \left(0.18*10^{-4}\right)* AD_{jt}^2 - \left(0.59*10^{-2}\right)* AD_{jt} * IR_j - \left(0.37*10^{-3}\right)* AD_{jt} * GC_j \\ &+ \left(0.86*10^{-2}\right)* AD_{jt} * OIL_j + \hat{c}_j + \hat{\varepsilon}_{jt} \end{aligned}$$

(6)
$$\begin{aligned} v_{jt} = &\ 884.86 + 0.65 * CD_{jt} - \left(0.15*10^{-3}\right)* CD_{jt}^2 - 22.00 * HD_{jt} + 53.36 * PR_{jt} \\ &+ \left(0.81*10^{-2}\right)* CD_{jt} * HD_{jt} + 0.57 * CD_{jt} * IR_j + 0.33 * CD_{jt} * GC_j \\ &- 0.65 * CD_{jt} * OIL_j + \hat{h}_j + \hat{v}_{jt} \end{aligned}$$

where j indexes region-cultivar pairings.[18] Changes in olive volume (v) are driven by changes in accumulated growing degree-days (CD), relative humidity (HD), precipitation (PR), the use of irrigation (IR), ground cover (GC), and cultivar type (OIL = 1 if Arbequina, Frantoio, Koroneiki, or Leccino). Changes in the uncontrolled damage rate (nd) are driven by changes in olive volume, the effect of which differs late in the growing

[17] The simulation equations differ from those presented in Cobourn et al. We estimate the fixed effects by location-cultivar pairing and define uncontrolled damage as the proportion of the sampled olive crop with visible ovipositional stings. For simplicity, the estimated specifications in **(5)** and **(6)** also exclude olive shape and minimum temperature variance variables, both of which are insignificant at any level in the original analysis.

[18] Equation **(5)** was estimated using the Tobit methodology with a lower limit of zero and an upper limit of one. The reported parameters are for a normally distributed random variable. Predictions less than zero were assigned a value of zero, and predictions greater than one were assigned a value of one in the simulation model to create density points consistent with observed damage rates.

season (*LATE* indicates dates after August 31), adult fly non-activity days (*AD*), irrigation, ground cover, and cultivar type.[19]

We use weather data over a 20-year period (1989 through 2008) to specify mean, minimum, and maximum daily temperatures, precipitation, and relative humidity for each location each day of the growing season. We estimate mean accumulated growing degree-days, mean accumulated adult fly non-activity days, mean relative humidity, and mean precipitation as fifth order polynomials in *t*. We also use **(5)** and **(6)** to specify the stochastic elements of **(3)** and **(4)**. We specify a bivariate normal distribution for the two error terms, each with mean and covariance matrix based on the residuals from estimation of **(5)** and **(6)**. Figure 1 displays densities for the estimated volume and uncontrolled infestation residuals. The former is aptly characterized by a normal distribution. Although the distribution of the latter is slightly skewed to the left, assuming a normal distribution is not an unreasonable starting point.

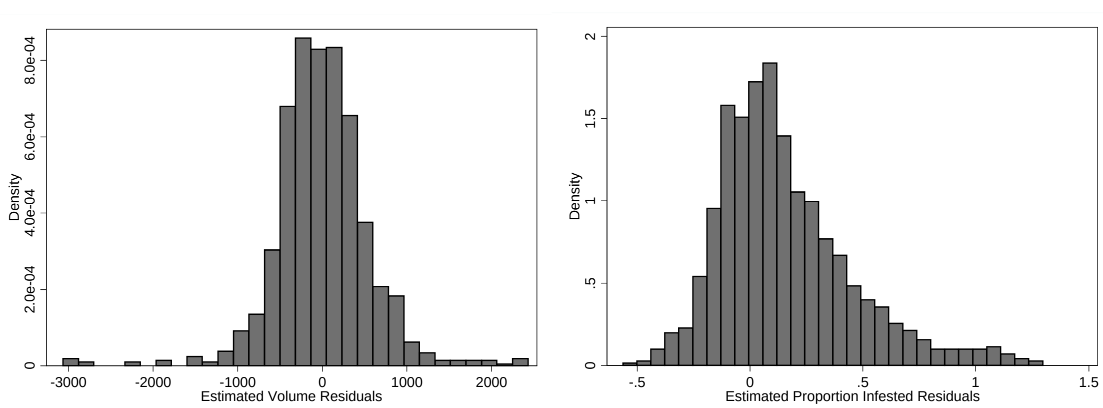

Figure 1. Probability Densities for Estimated Volume and Infestation Residuals

[19] Adult fly non-activity days are similar to degree-days in the sense that they track the amount of time that temperatures fall outside of fly activity thresholds, during which the fly will not damage fruit. However, they differ from degree-days in that they are not a measure of developmental time.

Each August, California's table and oil olive processors and the Olive Growers Council of California bargain on and set the prices to be paid by all processors for raw olives. There is a separate price schedule for each of two main groups of table olive cultivars. The first group contains the Manzanillo and Mission cultivars, among others. The second group contains Sevillano fruit. Each schedule specifies price premiums based on the average size of fruit in a delivery.[20] U.S. Department of Agriculture (USDA) grading standards specify olive size as a fruit count per unit weight. These fruit counts correspond with a range of fruit diameters. We estimate a relationship between diameter and volume for each of the table cultivars in our sample using ordinary least squares.[21] Table 2 reports the count, diameter, and estimated volume for each cultivar and size category. Table 3 lists the prices paid by processors for raw olives in 2008.

In order to specify *py*, we use yield estimates from growing seasons prior to the olive fruit fly infestation (Sibbett and Ferguson 2005). Olive yield increases over the course of the season until the fruit reach maturity. After that point, yield in terms of total weight plateaus while olives continue to increase in size. After the traditional harvest date, yield declines due to "overripeness, drying wind, and cold damage" (p.135, *ibid*.). We model the potential yield trajectory as increasing linearly from fruit set until maturity. We assume that the first date of maturity for table olives is September 1 and the first date of maturity for oil olives is October 1. After these dates, yield equals its historical

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[20] In practice, the specification of size for a delivery of fruit depends on both the average size and the size variance on the downside.

[21] We estimate the minimum, maximum, and mean volume associated with each fruit diameter measure in Table 4.2 by using the estimated regression coefficient and the bounds on a 95 percent confidence interval. Using this approach, the ends of the size intervals overlap. We use the midpoint of the max/min overlap between two categories to define the volume cutoff point for each size class. The data on host characteristics are from the dataset used for estimation by Cobourn et al. (2008).

Table 2. Olive Size Categories

	Count per lb.			Estimated Volume (100 mm^3)		
Designation	Manz., Mission	Sevillano	Diameter (mm)	Manz.	Mission	Sevillano
Sub-petite	>180	n/a	<12	<18	<15	n/a
Petite	141-180	n/a	12-15	18-24	15-20	n/a
Small	128-140	n/a	16-17	24-27	20-22.5	n/a
Medium	106-127	n/a	17-19	27-30	22.5-25	n/a
Large	91-105	n/a	19-20	30-31.5	25-26.5	n/a
Extra Large	65-90	65-75	20-22	31.5-34.5	26.5-29	61.5-67.5
Ex. Lg. 'L'	n/a	76-90	20-21	n/a	n/a	61.5-64.5
Ex. Lg. 'C'	n/a	65-75	21-22	n/a	n/a	64.5-67.5
Jumbo	47-60	47-60	22-24	34.5-37.5	29-31.5	67.5-73.5
Colossal	33-46	33-46	24-26	37.5-40.5	31.5-34	73.5-79
Super Colossal	<32	<32	>26	>40.5	>34	>79

Source: Agricultural Marketing Service (2004, 2007).

Table 3. Olive Prices

Table Olives				Oil Olives	
Manzanillo and Mission		Sevillano			
Size Class	Price ($/ton)	Size Class	Price ($/ton)	Price ($/ton)	
Undersize/Cull	10	Undersize/Cull	10	All	450
Sub-Petite	350	Extra Large 'L'	300		
Petite	400	Extra Large 'C'	350		
Small	650	Jumbo/Colossal/ Super Colossal	1050		
Medium/Large/ Extra Large	1210				

Source: California Olive Council (2008).

average of five tons per acre (National Agricultural Statistics Service 1990-2009). After the median historically-optimal harvest date for each region-cultivar pairing, as listed in table 4, yield declines linearly to zero by the model's terminal date. Fruit monotonically increase in size until harvest.

We assume a pesticide efficacy rate of 95.5 percent as in table 1 (2007). We initially assume a pesticide efficacy interval of seven days, which corresponds to current University of California IPM treatment recommendations. We test the model's sensitivity to the length of this interval. According to University of California Davis cost studies, one application to every other row of trees costs 10 dollars per acre (Krueger et al. 2004; O'Connell et al. 2005). All other costs of production are also taken from University of California Extension publications.[22]

Results

In table 4, we present the baseline model results when no pest control inputs are used and fruit is harvested at the traditional date. We average the first date of infestation, the fly infestation rate at harvest, and yield loss over 100 draws of the multivariate normally distributed error terms for each *t*. The percent yield loss at harvest represents the maximum yield loss assuming that all fruit damaged prior to harvest drop prematurely from the tree.

The first date of infestation differs substantially between cultivars. For Sevillano olives, first infestation occurs shortly after fruit set in mid-April. Sevillano fruit are the largest and fastest-growing of all olive cultivars grown in California, so this result is as expected. Manzanillo olives are also large and become susceptible to fly infestation from

[22] We assume that a grower operates a mature orchard (all trees exceed eight years of age).

late April through mid-June. Mission olives, which are smaller than other table olives but larger than the oil cultivars, become infested in mid-June through mid-July, on average. Among the oil olives considered, the high-density cultivars are the largest in size. Not surprisingly, they become infested earlier than the smaller, super-high density oil cultivars. The smallest of all cultivars, the super high-density Arbequina and Koroneiki varieties, do not exhibit signs of infestation until mid-August at the earliest.

Table 4. Uncontrolled Yield Loss with Traditional Harvest Timing

Region[a]	Cultivar	Traditional Harvest Date	Date of First Infestation	Maximum Yield Loss (%)
Super High-Density Oil Olives				
III	Arbequina	304 (Dec. 1)	195 (Aug. 14)	27.4
III	Koroneiki	304 (Dec. 1)	211 (Aug. 30)	22.4
High-Density Oil Olives				
III	Frantoio	304 (Dec. 1)	185 (Aug. 4)	39.4
I	Leccino	304 (Dec. 1)	129 (Jun. 9)	53.1
III	Leccino	304 (Dec. 1)	166 (Jul. 16)	46.5
Table Olives				
II	Manzanillo	262 (Oct. 20)	138 (Jun. 18)	100.0
III	Manzanillo	262 (Oct. 20)	139 (Jun. 19)	67.0
VI	Manzanillo	258 (Oct. 16)	134 (Jun. 14)	66.5
IV	Manzanillo	262 (Oct. 20)	88 (Apr. 29)	69.4
II	Mission	247 (Oct. 5)	160 (Jul. 10)	8.8
III	Mission	247 (Oct. 5)	167 (Jul. 17)	40.9
V	Mission	247 (Oct. 5)	152 (Jul. 2)	9.2
VII	Mission	278 (Nov. 5)	152 (Jul. 2)	24.2
IV	Mission	247 (Oct. 5)	134 (Jun. 14)	13.5
III	Sevillano	262 (Oct. 20)	79 (Apr. 19)	85.4

[a]Sierra Foothills (I), Northern Sacramento Valley (II), Southern Coastal Sacramento Valley (III), Southern Inland Sacramento Valley (IV), Northern Coast (V), San Joaquin Valley (VI), Southern Coast (VII).

There is little information on uncontrolled damage rates by cultivar, which makes validating the baseline difficult. Burrack (2007) suggests a range of uncontrolled damage of 10 to 30 percent for oil cultivars based on 2005 data. Relative to these estimates, the baseline model seems to overstate damage rates for oil olives. However, this estimate is extremely sensitive to date on which damage is measured because the majority of damage for oil olives occurs very late in the growing season. If we move the harvest date forward by even a week, the damage rate falls dramatically. Because we lack data on uncontrolled damage across years and the relative magnitude of the damage rates across cultivars matches Burrack (2007), we deem this an apt baseline for the analysis.

For table olive cultivars, Burrack (2007) estimates losses of 18 to 68 percent for Manzanillo olives, eight to 81 percent for Mission olives, and 80 to 100 percent for Sevillano olives. All of the estimates produced by the baseline model fall within or very close to these ranges. The only aberration of note is the damage rate of 100 percent for Manzanillo olives in Region II. Region II observations were taken from Butte County, which is home to a number of abandoned orchards. The fly population has flourished as a result, which would contribute to inflated damage rates area-wide.

Table 5 displays the optimal treatment strategy for a grower producing a given cultivar in a given region. The table displays the model results with the exogenous, traditional harvest date by region and cultivar and with the endogenously optimal harvest date with fly infestation. Because olive size increases until harvest, leading to rapidly increasing infestation rates, the optimal harvest date falls earlier in the season than the traditional date. The only exception to the rule is for Sevillano olives, for which harvest is optimally delayed by four days. However, this date falls within the range of traditional harvest dates for Sevillano olives. Thus, the results from the two models are equivalent.

Across region-cultivar pairings in table 5, allowing for flexibility in harvest timing alters the optimal pattern of pest control treatments. In several cases, endogenizing harvest pushes the optimal date of the first treatment forward in time, essentially lowering the economic threshold over which insecticide treatments increase profits. An earlier harvest date, relative to the traditional date, also eliminates pest control applications late in the growing season. For Leccino olives in Region I, no damage treatments accompany an earlier harvest date. For several table olive varieties, the change in harvest date eliminates the need for up to four weekly sprayings. It is also interesting to note that, when harvest is exogenous, there are weeks in which a grower will optimally skip damage control treatments (spraying at t = 188 for Manzanillo olives in Region III and t = 218 for Manzanillo olives in Region IV). Endogenizing harvest timing lowers the economic threshold for spraying and fills in these gaps in the joint treatment-harvest model. Further, for Sevillano olives, sprayings optimally extend later into the season.

For table olives, a change in harvest timing alters the expected size of olive fruit at harvest and the expected price. This alters the value of yield losses due to fly damage. As yield losses become more or less expensive in terms of lost profit, the grower alters his treatment decisions, which affect the damage trajectory and yield losses. The extent of yield losses over the season in turn determines the optimal date of harvest. The rationale for optimal oil olive harvest timing and treatment differs because oil olives do not receive a price premium. Oil olive growers optimally harvest at the earliest date of fruit maturity because yield losses increase monotonically over the growing season.

Table 5. Optimal Treatment Dates under Fixed and Flexible Harvest Timing

Region[a]	Cultivar	Model	Optimal Treatment Dates	Harvest Date
Super High-Density Oil Olives				
III	Arbequina	Fixed Harvest	196,299	304 (Dec. 1)
		Flexible Harvest	194	243 (Oct. 1)
III	Koroneiki	Fixed Harvest	212,301	304 (Dec. 1)
		Flexible Harvest	210	243 (Oct. 1)
High-Density Oil Olives				
III	Frantoio	Fixed Harvest	187,291,298	304 (Dec. 1)
		Flexible Harvest	185	243 (Oct. 1)
I	Leccino	Fixed Harvest	276,283,294,301	304 (Dec. 1)
		Flexible Harvest	no treatment	243 (Oct. 1)
III	Leccino	Fixed Harvest	167,286,297,304	304 (Dec. 1)
		Flexible Harvest	166	243 (Oct. 1)
Table Olives				
II	Manzanillo	Fixed Harvest	136,137,144,151,158,165,172,179,186,193	262 (Oct. 20)
		Flexible Harvest	136,137,144,151,158,165,172,179,186,193	228 (Sep. 16)
III	Manzanillo	Fixed Harvest	139,146,153,160,167,174,181,195,202,209,216,223,230,237,244,251	262 (Oct. 20)
		Flexible Harvest	139,146,153,160,167,174,181,188,195,202,209,216,223	228 (Sep. 16)
VI	Manzanillo	Fixed Harvest	135,163,170,177,184,191,198,205,212,220,227,234,241,248,255	258 (Oct. 16)
		Flexible Harvest	135,163,170,177,184,191,198,205,212,220,227	228 (Sep. 16)

Table 5. Continued

Table Olives, Continued				
IV	Manzanillo	Fixed Harvest	141,148,155,162,169,176,183,190,197,204,211,225,232,239,246,253,260	262 (Oct. 20)
		Flexible Harvest	141,148,155,162,169,176,183,190,197,204,211,218,225	228 (Sep. 16)
II	Mission	Fixed Harvest	206	247 (Oct. 5)
		Flexible Harvest	206	228 (Sep. 16)
III	Mission	Fixed Harvest	167,174,181,188,195,202,209,216,223,230,237,244	247 (Oct. 5)
		Flexible Harvest	167,174,181,188,195,202,209,216,223	228 (Sep. 16)
V	Mission	Fixed Harvest	no treatment	247 (Oct. 5)
		Flexible Harvest	no treatment	228 (Sep. 16)
VII	Mission	Fixed Harvest	152,189,203,210,233,240,247	278 (Nov. 5)
		Flexible Harvest	152,189,203,210	228 (Sep. 16)
IV	Mission	Fixed Harvest	192,199,206	247 (Oct. 5)
		Flexible Harvest	192,199,206	228 (Sep. 16)
III	Sevillano	Fixed Harvest	139,146,153,160,167,174,181,188,195,202,209,216,223,230,237	262 (Oct. 20)
		Flexible Harvest	134,141,148,155,162,169,176,183,190,197,204,211,218,225,232,239,246	266 (Oct. 24)

[a]Sierra Foothills (I), Northern Sacramento Valley (II), Southern Coastal Sacramento Valley (III), Southern Inland Sacramento Valley (IV), Northern Coast (V), San Joaquin Valley (VI), Southern Coast (VII).

Table 6. Yield Loss with Fixed and Flexible Harvest Timing

		Maximum Yield Loss (%)			
Region[a]	Cultivar	Fixed Harvest		Endogenous Harvest	
		Uncontrolled	w/ Treatment	Uncontrolled	w/ Treatment
Super High-Density Oil Olives					
III	Arbequina	27.4	21.3	11.2	7.6
III	Koroneiki	22.4	20.1	7.8	4.7
High-Density Oil Olives					
III	Frantoio	39.4	23.8	18.7	12.7
I	Leccino	53.1	34.5	29.5	29.5
III	Leccino	46.5	30.5	24.6	20.3
Table Olives					
II	Manzanillo	100.0	5.9	97.8	3.6
III	Manzanillo	67.0	2.1	59.6	1.2
VI	Manzanillo	66.5	6.4	26.6	5.6
IV	Manzanillo	69.4	13.7	61.8	13.6
II	Mission	8.8	6.8	7.5	5.5
III	Mission	40.9	0.8	36.7	0.7
V	Mission	9.2	8.5	7.8	7.1
VII	Mission	24.2	9.7	16.5	6.3
IV	Mission	13.5	8.1	11.8	6.5
III	Sevillano	85.4	26.3	86.0	21.9

[a]Sierra Foothills (I), Northern Sacramento Valley (II), Southern Coastal Sacramento Valley (III), Southern Inland Sacramento Valley (IV), Northern Coast (V), San Joaquin Valley (VI), Southern Coast (VII).

For most of the table olive cultivars, optimal treatment involves spraying every seven days, or at the end of the interval over which GF-120 bait remains effective. Reducing the efficacy interval to three days narrows the treatment intervals, but does not change the total number of days over which treatment is optimal, thus increasing the total number of sprays.[23] The optimal harvest date does not change from that listed in Table 5. An increase in the percent damage abatement from an insecticide application reduces the

[23] However, with reductions in the duration of pesticide efficacy, the spray limitations set by CDPR become binding. We do not consider the effect of this regulation in this analysis, though we expect it to reduce producer welfare as in the analysis by McKee et al. (2009).

optimal number of sprays, and pushes their dates later into the growing season. This last result seems counterintuitive, but agrees with Lichtenberg and Zilberman (1986).[24]

The results presented are the optimal treatment and harvest timing decisions when no quality constraints are included in the grower's optimization calculus. California's canning processors have a zero-tolerance policy for infested olives. The threshold for fly infestation in canning olives in Europe is one percent. A 95.5 percent efficacy rate for GF-120 is not sufficient, under average weather conditions, to suppress damage over the growing season to one percent for most table cultivars.[25] The exception is Mission olives from Region III, for which optimal treatment leads to average damage less than the canning processor threshold. However, anecdotal evidence suggests that increased temperatures have suppressed damage rates further, allowing producers to meet canning quality standards in recent years (Hearden 2009). Sensitivity analysis supports this result: an increase in mean temperature over the season reduces fly damage and yield losses.

The oil industry, as a rule of thumb, considers ten percent damage the threshold below which fly infestation has a negligible effect on the sensory characteristics of olive oil (Vossen, Varela, and Devarenne 2005). With the optimal treatment-harvest combination, super high-density cultivars exhibit less than the threshold level of damage at harvest. Additionally, all Mission cultivars exhibit less than ten percent damage at harvest with or without treatments. Although Mission olives have historically been a table cultivar, they have a high enough oil content to work well for oil processing too. (Sibbett and Ferguson 2005)

[24] As explained in the literature review, they show that a decrease in the marginal productivity of an insecticide leads to an increase in the number of treatments.
[25] With a proportional reduction in damage levels from the insecticide, it is impossible to achieve a zero level of infestation if the uncontrolled damage level is at any point greater than zero.

Conclusions

Our empirical analysis demonstrates the impact of changes in harvest timing on grower-level optimal treatment decisions. While the example is specific to the olive fruit fly, the results and the modeling approach hold implications for studies of pest management in general. Harvest timing may not always be flexible, but the analysis applies in any case where inputs affect productivity directly through yield and/or quality and indirectly via damage abatement. Our results suggest that there is a cost to treating those inputs as fixed when determining optimal treatment timing. In this paper, treating harvest timing as fixed overstates the total cost of treatment and the losses to producers from infestation. In general this bias may operate in either direction depending on the relationships among positive inputs, yield/quality, and damage abatement (Saha, Shumway, and Havenner 2007).

Another issue that the analysis touches upon, and which we intend to examine more thoroughly in the future, is the optimal choice of treatment and harvest under processor-imposed quality standards. Without quality standards, the grower optimizes treatment and harvest timing in such a way as to maximize yield. With quality standards the grower's treatment plan will reflect the relatively greater importance of suppressing the level of damage so that all revenue is not lost. We do not consider quality thresholds herein because the efficacy of GF-120 treatments depends, in part, on the pest control practices used by all producers in a region. In a future analysis, we intend to formulate a region-wide stochastic dynamic programming model with quality thresholds to determine socially optimal treatment and harvest practices in the presence of stock externalities.

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