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The Effect of Quality Assurance Policies for Processing Tomatoes on the Demand for Pesticides

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In California, acceptance sampling is used to monitor the quality of processing tomatoes delivered by growers to processors. A proposal to change the current quality assurance policy was recently put forth to reduce the growers' incentive to use pesticides. In this article we examine the effect of alternative quality assurance policies on a profit-maximizing grower's demand for pesticides. The results indicate that the demand for pesticides is sensitive to changes in the quality assurance policy and that the proposed policy would reduce the optimal level of pesticide use on processing tomatoes. Disregarding the impact of quality assurance policy may be the reason that the demand for pesticides has been underestimated so often in the past.

Key words: pesticides, processing tomatoes, quality assurance.

Introduction

The California processing tomato industry recently considered a proposal to increase the acceptable level of insect damage in delivered loads of tomatoes from 2% to 3% by weight. The objective of this proposed policy change was to reduce the growers' motivation to use insecticides. Although processing tomato growers strongly supported the change, processors felt that the increased tolerance would adversely affect the quality, or at least the perceived quality, of California's processed tomato products. The proposal was rejected on this basis.

A question that was never resolved is whether or not the increased tolerance would actually result in less pesticide use. The new policy was supposed to reduce the grower's motivation to use pesticides by making it easier to get insect-damaged tomatoes accepted. California processing tomato growers get most of their loads accepted under the current quality assurance policy by delivering loads with damage levels far below the contract specifications. Even though integrated pest management (IPM) recommendations for pesticide applications are based on a target of 2% damage at harvest (Wilson et al.), most loads of processing tomatoes in California show only a trace of insect damage—far below the 2% maximum allowable. In 1990, only 56 of 380,822 inspected loads were rejected because of insect damage (California Processing Tomato Advisory Board).

Given the public's continuing concern about the use of chemicals in food production, quality assurance policy and its effect on the use of pesticides is likely to be a recurring issue. Unfortunately, quality assurance policy is overlooked in most research concerning pesticide productivity.

In this study, we present a model of a profit-maximizing processing tomato grower who produces tomatoes with stochastic quality which are inspected using acceptance sampling. We use the model to find the grower's profit-maximizing level of pesticide use. The effect

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of alternative quality assurance policies is examined using numerical analysis. In addition to the proposed increase in tolerance from 2% to 3%, we consider three other quality assurance policies. These policy alternatives are designed to reduce the value or increase the cost of using pesticides to reduce insect damage.

In the next section, the model is developed using concepts from both microeconomic analysis and acceptance sampling theory. The validity of the model is then established by comparing the model's solution with the limited data we have on the use of pesticides in processing tomato production. The model is solved under a variety of policy alternatives in the succeeding section, and last, some conclusions are drawn.

The Model

The grower's objective is to maximize expected profit. Profit is a random variable because the grower's revenue per load, R, depends upon whether or not a load is accepted:

$$R = \begin{cases} rL & \text{if accepted} \\ 0 & \text{if rejected,} \end{cases} \tag{1}$$

where r is the contribution margin of the load (\$/ton) excluding the cost of pest control, and L is the size of the load (tons). The conditional probability, $P(A \mid \phi)$, represents the probability that a load is accepted (event A) when the proportion damaged in the load is ϕ. The proportion damaged in the load, ϕ, is a random variable following the joint probability density function, $h(\phi, x)$, where x is the number of pesticide applications. We can write the marginal probability of acceptance for a given number of pesticide applications as:

$$P_A(x) = \int_0^1 P(A \mid \phi)h(\phi, x)\, d\phi. \tag{2}$$

Expected profit for the whole farm depends on the cost of applying pesticides to the whole farm, $C(x)$, and on total production. We assume that yield is independent of pesticide use because the most common processing tomato pest, *Heliothis zea* (*H. zea*) or tomato fruitworm, typically attacks the fruit and not the plant (Statewide Integrated Pest Management Project). We also assume that the pesticide does not affect the plant. If Y is total production (tons) and L is the size of a load (tons/load), the number of loads submitted for inspection is Y/L, and the expected profit for the whole farm is:

$$\begin{aligned} \pi(x) &= P_A(x)rLY/L - C(x), \\ &= P_A(x)rY - C(x). \end{aligned} \tag{3}$$

The Quality Assurance Policy

The conditional probability of acceptance, $P(A \mid \phi)$, is defined by the quality assurance policy. Most analyses of pesticide productivity assume 100% inspection, implying that every bad unit can be identified and isolated, and that $P(A \mid \phi) = 1 - \phi$ (e.g., Headley; Campbell; Lichtenberg and Zilberman; Babcock, Lichtenberg, and Zilberman). This is rarely the case in agricultural production systems, and it is certainly not the case with processing tomatoes, because testing for worm damage is destructive. The more common quality assurance policy is the use of sampling inspection. With sampling inspection, the characteristics of a randomly drawn sample are used to determine the fate of a submitted load.

Processing tomatoes are evaluated using a double-sample inspection plan. A typical double-sample inspection policy involves drawing a sample of size n_1, accepting the load if the number of defectives in the sample is no more than c_1, and rejecting the load if the number of defectives is more than c_2 ($c_2 > c_1$). If the number of defectives is more than

c_1 and no more than c_2, a second sample of size n_2 is drawn and the load is accepted if the sum of the defectives from the first and second samples is no more than c_3, where $c_3 \geq c_2$ (see Montgomery for a detailed description of double-sample inspection policies). With this quality assurance policy, the conditional probability of acceptance is:

$$P(A \mid \phi) = \sum_{d_1=0}^{c_1} f(d_1 \mid n_1, \phi) + \sum_{d_1=c_1+1}^{c_2} \sum_{d_2=0}^{c_3-d_1} f(d_1 \mid n_1, \phi) f(d_2 \mid n_2, \phi), \tag{4}$$

where $f(d_i \mid n_i, \phi)$ is the probability of observing d_i defectives in a sample of size n_i, given that the proportion defective in the load is ϕ.

The exact distribution of the number of defectives in a sample is hypergeometric, but if the sample size is small relative to the size of the load, a binomial approximation to the hypergeometric distribution can be used (Montgomery, pp. 36–39). Since processing tomato loads are about 25 tons and the samples are 100 pounds, we can safely use the binomial approximation:

$$f(d_i \mid n_i, \phi) = \binom{n_i}{d_i} \phi^{d_i}(1 - \phi)^{n_i - d_i}. \tag{5}$$

The Prior Distribution

The most difficult relationship to define in this model is the prior distribution of quality, $h(\phi, x)$. The exact shape of $h(\phi, x)$ depends on the location of the field, the tomato variety, and the maturity date (late maturing varieties are more prone to infestation). Some growers have consistently low damage levels, while others face chronic infestations. To estimate $h(\phi, x)$, we would need to acquire data that relate x, the level of pesticide use, to ϕ, the proportion damaged in loads. These data would be expensive to collect since ϕ is a measure of the actual proportion damaged in a load and therefore requires the inspection of each tomato. Recently, the California Processing Tomato Advisory Board began collecting data on pesticide use, but its surveys are not matched to damage levels.

We can get an idea of the range of the distribution of ϕ, when no damage control efforts are undertaken ($x = 0$), from the trials performed by Zalom, Wilson, and Hoffman. They examined the effect of the timing of infestations by *H. zea,* the intensity of infestations, and tomato variety on the proportion damaged at harvest. The results of their experiments indicate that the mean proportion damaged at harvest is between 1 and 3% when no damage control efforts are undertaken. The maximum mean proportion damaged was about 6%.

Some information about the shape of $h(\phi, x)$ can be gleaned from the inspection data collected by the California Processing Tomato Advisory Board. Of all the loads graded in 1990, 97.9% had no worm damage or only trace damage in samples, 99.7% had .5% or less damage in samples, and 99.9% had 1% damage or less in samples. Unfortunately, these data represent the sampling distribution of damage after pesticides have been used. They support, however, a common assumption among growers and processors that most loads have little or no damage and that the frequency of high damage levels is relatively low (i.e., the distribution of quality has an exponential shape).

We assume that when $x = 0$, the damage level at harvest (ϕ) follows a rescaled beta distribution with parameters $(\alpha, \beta) = (1, 4)$. These parameters give the beta distribution an exponential shape. To test the sensitivity of the results to the shape of the distribution, we also solve the model with $(\alpha, \beta) = (6, 6)$, which gives the ϕ distribution an approximately normal shape, and with $(\alpha, \beta) = (1, 1)$, which gives the ϕ distribution a uniform shape. The beta distribution was chosen because it is often used to represent the prior distribution in studies of quality assurance policy (e.g., Moskowitz and Plante; Stuart, Montgomery, and Heikes). The beta distribution can represent a wide variety of shapes, it is tractable, and the distribution of defectives in samples, d, is relatively insensitive to misestimation of the beta distribution's parameters (Weiler).

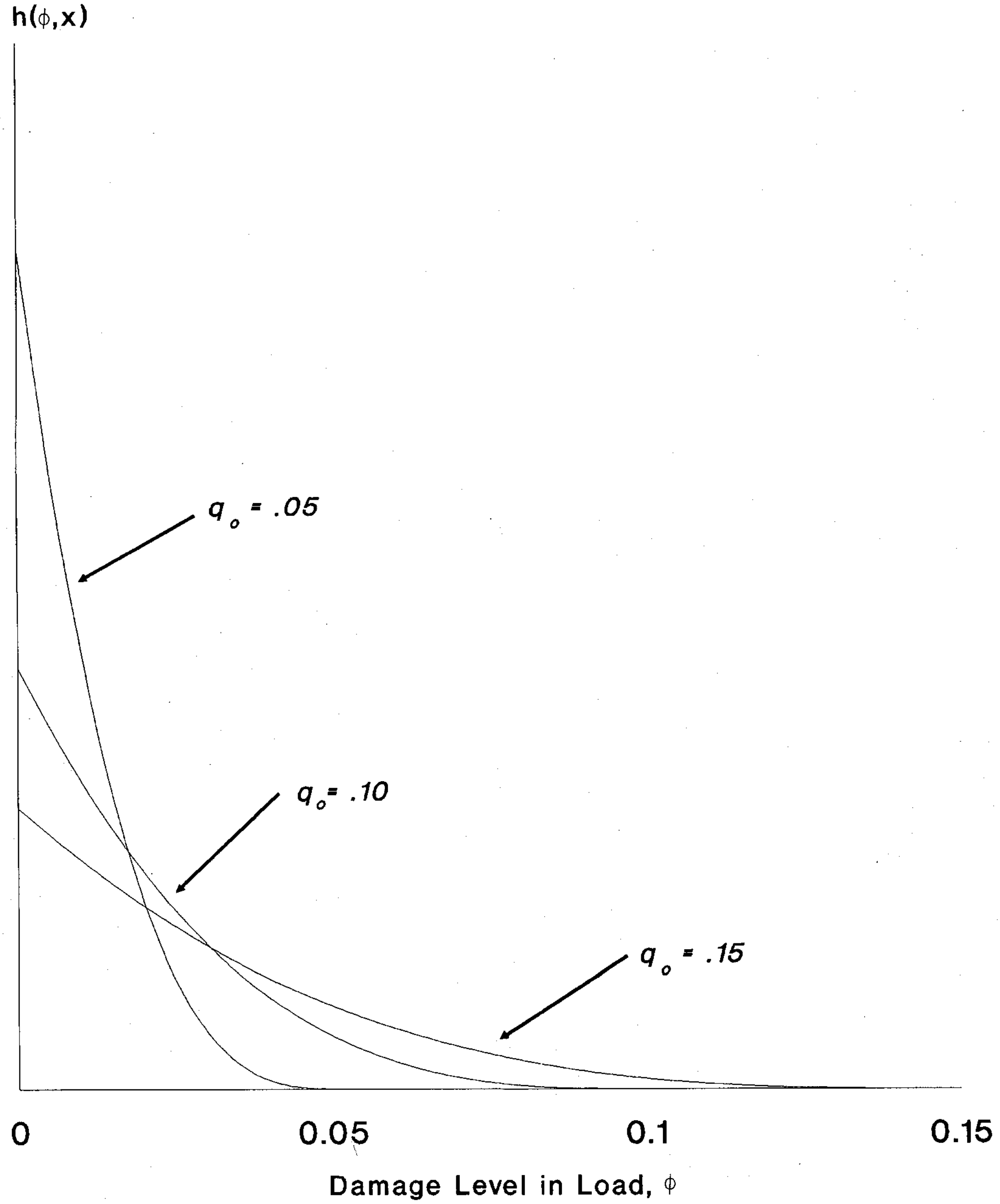
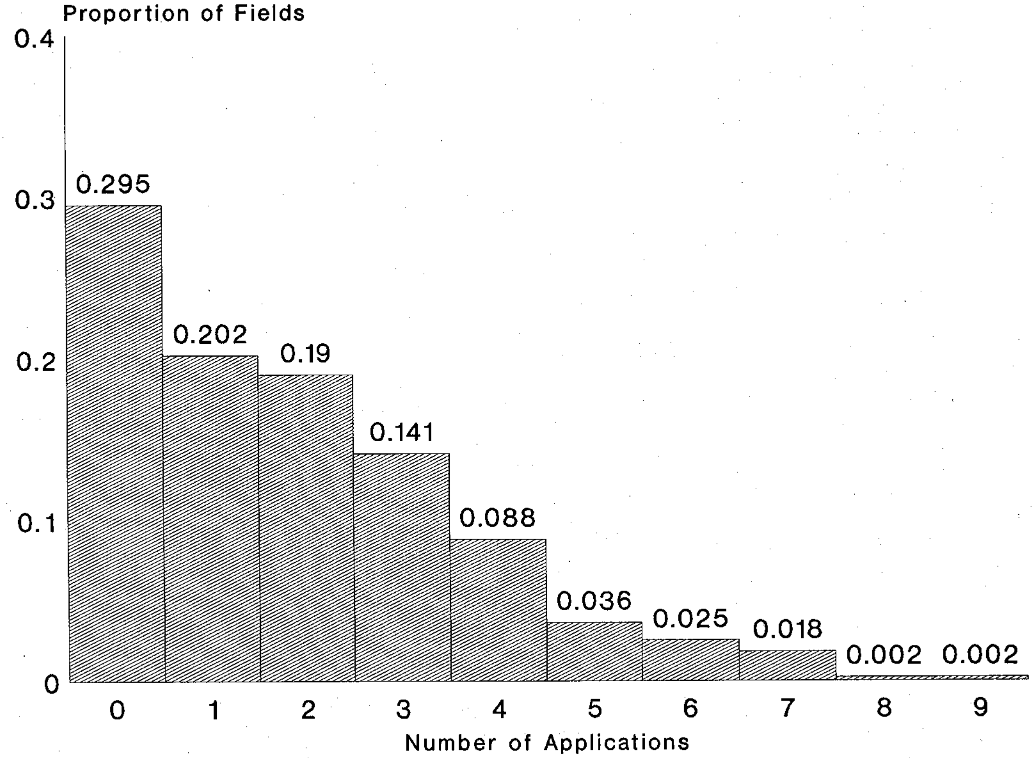


Figure 1. Distribution of ϕ at different levels of susceptibility to infestation when $x = 0$

To represent different degrees of susceptibility to infestations, we define three distributions of ϕ when $x = 0$. We rescale the beta distribution from [0, 1] to [0, q_o] (q_o represents maximum damage level when no pesticides are used, i.e., when $x = 0$), where $q_o = .05$ represents low susceptibility, $q_o = .10$ represents moderate susceptibility, and $q_o = .15$ represents high susceptibility to infestations. When $(\alpha, \beta) = (1, 4)$ and $x = 0$, the mean damage is .01 for the low-susceptibility grower, .02 for the moderate-susceptibility grower, and .03 for the high-susceptibility grower. These means are consistent with the results of Zalom, Wilson, and Hoffman. These three distributions are illustrated in figure 1 for the case of $(\alpha, \beta) = (1, 4)$.



Source: California Tomato Growers Assoc.

Figure 2. Frequency of pesticide applications in 1989

The Quality Improvement Function

We assume that efforts directed toward controlling insect damage shift the distribution of ϕ toward zero damage, in effect rescaling $h(\phi, x)$ over a smaller range with a maximum closer to zero. The effect of pesticide applications, x, is defined by a quality improvement function, $q(x)$, where $q(x)$ is the maximum damage level at different values of x [q_o is the maximum damage level for the special case of $x = 0$, i. e., $q(0) = q_o$]. Although no estimates of $q(x)$ are available, we assume that $q'(x) < 0$ and that $q''(x) > 0$, over the relevant range of x. We can get an idea of the relevant range of x from surveys conducted by the California Tomato Growers Association. In the 1989 growing season, the number of insecticide treatments applied by surveyed growers ranged from zero to nine. The distribution of applications in 1989 is shown in figure 2 (California Tomato Growers Association).

We assume that the quality improvement function has an exponential form, $q(x) = q_o\text{EXP}(-\lambda x)$, where λ is a parameter defined by the effectiveness of the pesticide. This is the functional form used by Harper and Zilberman to relate pounds of pesticide used to percentage yield lost due to pest damage. We define three values of λ corresponding to pesticides with low effectiveness ($\lambda = .4$), moderate effectiveness ($\lambda = .6$), and high effectiveness ($\lambda = .8$). The values of $q(x)$ for the three levels of pesticide effectiveness are shown in figure 3.

Other Parameters

The model assumes that the grower operates a 700-acre farm in Yolo County, California, and that the yield is the 1990 statewide average of 30 tons per acre. The contribution margin, excluding worm-control costs, is \$7.42 per ton. Worm-control costs are \$24.76

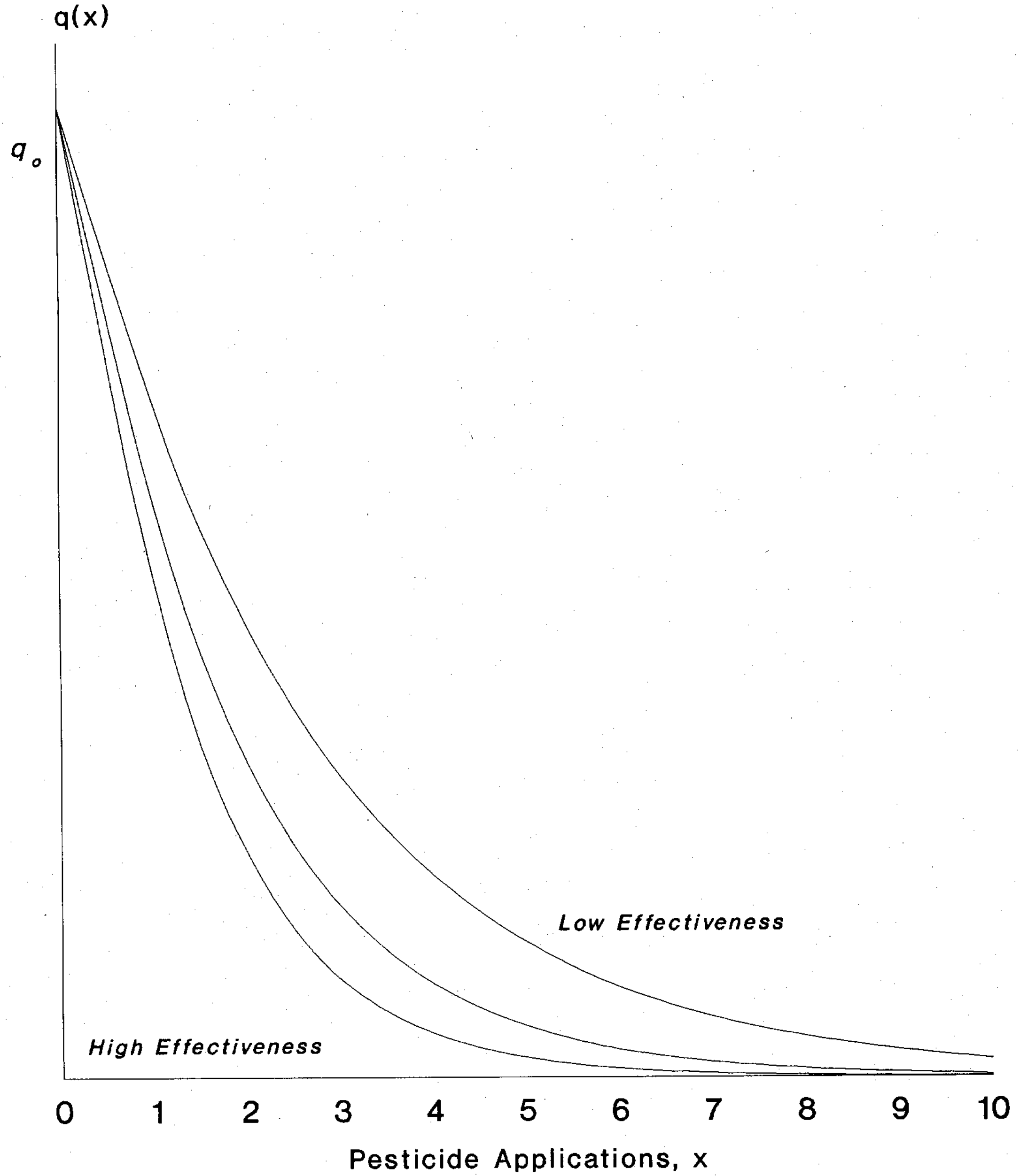


Figure 3. Quality improvement functions for different levels of pesticide effectiveness

per application per acre, or about $.83 per application per ton (Yolo County Cooperative Extension Service). In addition, we assume that tomatoes are shipped in 25-ton loads and that the grower is paid for 25 tons, regardless of whether one or two samples are drawn.

Model Validity

To test the validity of the model, the optimal number of pesticide applications was calculated for the three levels of susceptibility and the three levels of pesticide effectiveness

Table 1. Optimal Number of Pesticide Applications under the Current Quality Assurance Policy

Pesticide Effectiveness (λ):	.8	.8	.8	.6	.6	.6	.4	.4	.4
Field Susceptibility (q_o):	.05	.10	.15	.05	.10	.15	.05	.10	.15
Optimal No. of Applications (x*)	1	2	2	1	2	3	2	3	4
Mean Damage Level, given x*	.0045	.0040	.0061	.0055	.0060	.0050	.0045	.0060	.0061
Prob. of Acceptance, given x*	.9983	.9994	.9860	.9923	.9865	.9962	.9983	.9865	.9860
Consumer's Risk, given x*	.0001	<.0001	.0070	.0031	.0067	.0009	.0001	.0067	.0070
Producer's Risk, given x*	.0018	.0007	.0078	.0055	.0076	.0033	.0018	.0076	.0078

under the current quality assurance policy. Since the current policy is defined by weight, while the probability of acceptance is based on numbers of tomatoes [see equation (4)], we used a conversion factor of six tomatoes per pound to calculate the probability of acceptance. Under this assumption, $n_1 = n_2 = 600$ tomatoes (100 lbs.), $c_1 = 12$ tomatoes (2% of 100 lbs.), $c_2 = 18$ tomatoes (3% of 100 lbs.), and $c_3 = 24$ tomatoes (2% of 200 lbs.).

The optimal number of pesticide applications was found by calculating the expected profit [equation (3)] for integer values for the number of pesticide applications (x). The optimal number of pesticide applications, x*, the mean damage in delivered loads given x*, the probability of load acceptance given x*, and the consumer's and producer's risk given x* are shown in table 1 for all nine cases of pesticide effectiveness and susceptibility to infestation. The consumer's risk is the probability that a rejectable load is accepted,

$$R_c = \int_{.02}^{1} P(A \mid \phi)h(\phi, x)\, d\phi, \tag{6}$$

and the producer's risk is the probability that an acceptable load is rejected,

$$R_p = \int_{0}^{.02} (1 - P(A \mid \phi))h(\phi, x)\, d\phi. \tag{7}$$

The optimal numbers of applications shown in table 1 are within the range of pesticide use recorded by the California Tomato Growers Association in 1989 and 1990. Also, the optimal mean damage level is about .5%, which is consistent with the distribution of damage recorded by the California Processing Tomato Advisory Board in 1990. The results in table 1 should not be taken as recommendations for pesticide use, since they depend on the assumptions regarding susceptibility to infestations and pesticide effectiveness. However, they can be used as a baseline for measuring the effect of quality assurance policy changes on the optimal use of pesticides.

Policy Analysis

We consider four different quality assurance policy alternatives: increase tolerance from 2% to 3% damage (alternative A), increase the sample size from 100 pounds to 200 pounds (alternative B), place a 100% surcharge on the price of pesticides (alternative C), and 100% inspection (alternative D). Alternatives A and B are designed to reduce the value of pesticides to growers, while alternative C is designed to increase the cost of pesticides. Alternative D is the quality assurance policy that is implicitly assumed in most studies of pesticide productivity.

The optimal number of pesticide applications changes when the parameters of the ϕ distribution are changed from $(\alpha, \beta) = (1, 4)$ to either $(\alpha, \beta) = (6, 6)$ or $(\alpha, \beta) = (1, 1)$. The normally shaped beta distribution, $(\alpha, \beta) = (6, 6)$, and the uniformly shaped beta distribution, $(\alpha, \beta) = (1, 1)$, result in slightly higher optimal pesticide applications, because these distributions have higher densities at the higher levels of damage. These distributions also result in larger decreases in the optimal number of pesticide applications when compared to the exponentially shaped beta distribution. For example, when $(\alpha, \beta) = (6, 6)$, policy alternative A results in a one-application decrease in the optimum in all but one case. Our results show that the policy changes have a greater effect on pesticide usage when $(\alpha, \beta) = (6, 6)$ or $(\alpha, \beta) = (1, 1)$ than when $(\alpha, \beta) = (1, 4)$. To avoid overstating the effect of the proposed policy changes, the remainder of the results presented in this article are for an exponentially shaped beta distribution of ϕ, i.e., $(\alpha, \beta) = (1, 4)$.

Policy Alternative A*: Increased Tolerance*

Policy alternative A represents the policy modification recently considered by the California processing tomato industry. This modification would increase the tolerance for insect damage from 2% to 3% by weight. We assume that the same double-sample inspection procedure would be used under the new policy and that a second sample would be drawn if the first sample had between 3% and 4% damage. Under these assumptions, $n_1 = n_2 = 600$ tomatoes (100 lbs.), $c_1 = 18$ tomatoes (3% of 100 lbs.), $c_2 = 24$ tomatoes (4% of 100 lbs.), and $c_3 = 36$ tomatoes (3% of 200 lbs.).

This quality assurance policy results in the optimal pesticide applications shown in table 2. In five of the nine cases, the optimal number of pesticide applications is less under alternative A. Growers who use the most effective pesticides decrease the number of pesticide applications in one case, while growers who use the least effective pesticides reduce their pesticide use in all cases. These results imply that this proposed policy could indeed have an impact on the amount of pesticides used by processing tomato growers. Growers who are susceptible to infestation and who use less effective pesticides are most likely to reduce pesticide use because additional applications have a relatively low marginal value.

As one would expect, increasing the tolerance results in a slightly higher average damage level, increased consumer's risk, and decreased producer's risk. Alternative A significantly increases the probability that a processor will get a load with more than 2% damage. In this respect, the processor's concerns about the effect of this proposal on the quality of delivered tomatoes are not unfounded.

Policy Alternative B*: Doubling the Sample Size*

A common practice in many industries is to increase the sample size used in receiving inspection to improve the accuracy of inspection. Increasing the accuracy reduces the risk facing growers delivering acceptable loads, but increases the risk facing growers delivering rejectable loads. Theoretically, as the accuracy improves, growers submitting acceptable loads can relax their damage-control efforts, while growers submitting rejectable loads will strengthen their damage-control efforts.

Under alternative B, we double the sample size from 100 pounds to 200 pounds and maintain the tolerance level at 2% by weight, so $n_1 = n_2 = 1{,}200$ tomatoes, $c_1 = 24$ tomatoes (2% of 200 lbs.), $c_2 = 36$ tomatoes (3% of 200 lbs.), and $c_3 = 48$ tomatoes (2% of 400 lbs.). As shown in table 3, doubling the sample size has no effect on the optimal number of pesticide applications. The producer's and consumer's risks change very little under this alternative, because the increased accuracy from doubling the sample size is not very significant when the load size is so large.

Policy Alternative C*: 100% Surcharge*

This policy alternative differs from the others in that it is designed to affect the cost of reducing insect damage rather than the benefit associated with reducing insect damage. Although doubling the cost would have a tremendous effect on the use of most inputs, it seems to have a small effect on the optimal number of pesticide applications (table 4). In only one case does the 100% surcharge result in an effective reduction in the use of

Table 2. Optimal Number of Pesticide Applications under Policy Alternative *A*

Pesticide Effectiveness (λ): / Field Susceptibility (q_o):	.8 / .05	.8 / .10	.8 / .15	.6 / .05	.6 / .10	.6 / .15	.4 / .05	.4 / .10	.4 / .15
Optimal No. of Applications (x^*)	1	1	2	1	2	2	1	2	3
Mean Damage Level, given x^*	.0047	.0090	.0061	.0055	.0060	.0090	.0067	.0090	.0090
Prob. of Acceptance, given x^*	.9999+	.9879	.9997	.9999+	.9997	.9874	.9990	.9879	.9874
Consumer's Risk, given x^*	.0001	.0828	.0130	.0053	.0124	.0840	.0254	.0828	.0840
Producer's Risk, given x^*	<.0001	.0001	<.0001	<.0001	<.0001	.0001	<.0001	.0001	.0001

Table 3. Optimal Number of Pesticide Applications under Policy Alternative *B*

Pesticide Effectiveness (λ):	.8	.8	.8	.6	.6	.6	.4	.4	.4
Field Susceptibility (q_o):	.05	.10	.15	.05	.10	.15	.05	.10	.15
Optimal No. of Applications (x^*)	1	2	2	1	2	3	2	3	4
Mean Damage Level, given x^*	.0045	.0040	.0061	.0055	.0060	.0050	.0045	.0060	.0061
Prob. of Acceptance, given x^*	.9992	.9999	.9876	.9940	.9880	.9976	.9992	.9880	.9876
Consumer's Risk, given x^*	.0001	<.0001	.0060	.0027	.0058	.0008	.0001	.0058	.0060
Producer's Risk, given x^*	.0001	.0002	.0052	.0035	.0051	.0019	.0009	.0051	.0052

pesticides. In this one case, the reduction in the optimal application rate causes an increase in the average damage level which results in an increase in both the consumer's and producer's risk.

These results imply that the grower's demand for pesticides is very inelastic in the region of the optimum, and so policies that directly or indirectly affect the marginal cost of pesticides will be ineffective in reducing their use.

Policy Alternative D*: 100% Inspection*

The last policy alternative, 100% inspection, implies that every bad tomato can be identified and isolated and, therefore, $P(A \mid \phi) = 1 - \phi$. By substituting $P(A \mid \phi) = 1 - \phi$ for (4) in the model and solving, we get the optimal values presented in table 5.

In eight of the nine cases considered under alternative *D*, the optimal number of pesticide applications is 0. In all cases, 100% inspection results in a lower level of pesticide use than the current sampling inspection policy (table 1). With 100% inspection, a high proportion of delivered loads is accepted without using any pesticides, and so the value of pesticides is much less than when sampling inspection is used. In addition, provided the inspection is accurate, there is no consumer's or producer's risk because every tomato is examined individually; thus, there is no risk of accepting bad tomatoes or rejecting good tomatoes.

These results contribute to our understanding of why many growers appear to use more pesticides than are predicted by econometric analysis (see Campbell; Headley; Carrasco-Tauber and Moffit). If 100% inspection is assumed and sampling inspection actually used, then a model of grower behavior will severely undervalue pesticides and it will appear that growers apply far more pesticides than is warranted.

Conclusions

Several important conclusions can be drawn from this analysis. First, the proposal to increase the tolerance for insect damage is likely to result in less pesticide use by some expected profit-maximizing growers. This conclusion is based on the assumptions regarding: (*a*) the distribution of the damage level, $h(\phi, x)$, although the results appear robust

Table 4. Optimal Number of Pesticide Applications under Policy Alternative *C*

Pesticide Effectiveness (λ):	.8	.8	.8	.6	.6	.6	.4	.4	.4
Field Susceptibility (q_o):	.05	.10	.15	.05	.10	.15	.05	.10	.15
Optimal No. of Applications (x^*)	1	2	2	1	2	3	1	3	4
Mean Damage Level, given x^*	.0045	.0040	.0061	.0055	.0060	.0050	.0067	.0060	.0061
Prob. of Acceptance, given x^*	.9983	.9994	.9860	.9923	.9865	.9962	.9762	.9865	.9860
Consumer's Risk, given x^*	.0001	<.0001	.0071	.0031	.0067	.0009	.0128	.0067	.0070
Producer's Risk, given x^*	.0018	.0007	.0078	.0055	.0076	.0033	.0102	.0076	.0078

Table 5. Optimal Number of Pesticide Applications under Policy Alternative *D*

Pesticide Effectiveness (λ):	.8	.8	.8	.6	.6	.6	.4	.4	.4
Field Susceptibility (q_o):	.05	.10	.15	.05	.10	.15	.05	.10	.15
Optimal No. of Applications (x^*)	0	0	1	0	0	0	0	0	0
Mean Damage Level, given x^*	.0100	.0200	.0135	.0100	.0200	.0300	.0100	.0200	.0300
Prob. of Acceptance, given x^*	.9901	.9801	.9866	.9901	.9801	.9701	.9901	.9801	.9701
Consumer's Risk, given x^*	0	0	0	0	0	0	0	0	0
Producer's Risk, given x^*	0	0	0	0	0	0	0	0	0

with respect to this assumption; (*b*) the relationship between pesticide use and the damage level, $q(x)$; and (*c*) the level of susceptibility to infestation, q_o. In general, growers who use less effective pesticides and who are more susceptible to infestation are also more sensitive to changes in the quality assurance policy. Further research should be focused on specifying and estimating the functions $h(\phi, x)$ and $q(x)$.

Second, a grower's demand for pesticides appears to be very inelastic in the neighborhood of the optimal solution. This implies that efforts designed to increase the cost of pesticides are not likely to significantly reduce pesticide use. This conclusion calls into question the value of pesticide residue limitations which are designed to indirectly increase the cost of pesticide use. Finally, econometric models that assume 100% inspection when sampling inspection is actually used are likely to severely undervalue pesticides. This may be the reason that models developed by Headley, by Lichtenberg and Zilberman (see Carrasco-Tauber and Moffit), and by others do not accurately predict the demand for pesticides by farmers.

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