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Risk and Maximum Residue Limits: A Study of Hops Production

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Abstract

This paper examines how maximum residue limits (MRLs) affect the optimal choice by growers of chemical applications to control pests and diseases. In practice, growers who export balance both yield risk and pesticide residue uncertainty when making chemical application decisions. To address these issues we specify an expected utility model and calibrate it to data collected from a 2012 survey of hop growers in the Pacific Northwest. Then we simulate hop grower/exporter decisions subject to MRLs across a myriad of scenarios. As anticipated, risk preferences contribute to explaining higher chemical use. All else equal, more stringent MRLs tend to induce risk averse growers to apply fewer chemicals than do risk neutral growers because of the increasing likelihood of crop rejection due to exceeding an MRL. Under specific circumstances risk preferences coupled with underlying MRLs have the potential to tip the decision towards less chemical uses with potential for more growers implementing integrated pest management strategies or, alternatively, greater use of other pesticides not subject to MRL restrictions.

Keywords: expected utility, hop production, maximum residue limits, risk preferences

1. Introduction

Maximum residue limits (MRLs) are a maximum concentration of chemical residue to be legally permitted on food and agricultural products. MRLs are heterogeneous across countries and regions and can be applied in both domestic and international trade of food and agricultural products. Extensive literature exists on agricultural production from continuous stochastic income due to price or output uncertainty (e.g., Just & Zilberman, 1983; Babcock & Hennessy, 1996). In contrast this article develops a model of a grower's input decisions under yield risk and uncertain pesticide residue with MRL constraints imposed on exports. We specify a theoretical model that (i) incorporates the grower's risk preferences; (ii) emphasizes the role of MRLs under forward contracts (Note 1); and (iii) proposes a decision rule that balances both yield risk and pesticide residue. The simulation model illustrates hop production and exports in the Pacific Northwest. A wide range of scenarios are simulated to assess hop grower response to key production, trade, MRL, and policy parameters.

On one hand, hop growers face a substantial degree of production risk from pest/disease infestation. For example, during the 1998 season some growers experienced a 60% reduction in yield due to the two-spotted spider mite (TSSM) injury. Overall, Washington production was down an average of 10% in 1998 due to TSSM attack (Crop Profile for Hops in Washington, 2001). The disease powdery mildew can similarly reduce yield by up to 90% if left untreated (Mahaffee, Engelhard, Gent, & Grove, 2009); yield damage of 20% from omitting a fungicide application late in the season also been documented (Gent et al., 2014). On the other hand, hop growers/exporters increasingly face more stringent MRLs determined exogenously by importing countries.

The paper makes several primary contributions not present in the literature. First, it demonstrates tradeoffs that growers balance between yield risk and pesticide residues when using chemicals to control pests and diseases. Second, it addresses decisions for both risk neutral and risk averse growers. Third, it specifically examines decisions for hop production providing guidance to grower/exporters previously not available.

The remainder of the article is structured as follows. In the next section, we provide a theoretical model. This is followed by specification of the empirical model and simulation procedures. These simulations provide experimental evidence of hypothetical economic decisions and consequences. Results and implications are then provided. We end with concluding remarks and discuss future directions for research.

2. Theoretical Model

2.1 Hop Production and Marketing Process

We assume a stylized hop production and marketing timeline: contract stage, production stage and marketing stage. In the contract stage, the hop merchant (buyer) offers a multi-year forward contract (typically 3 to 5 years) that specifies the hop price per pound ($\overline{p}$), size of contract (i.e. purchase quantity) ($\overline{y}$), and the pesticide tolerance level ($\overline{q}$). Given a hop contract, the representative hop grower makes a decision on the choice of chemical levels at the beginning of the production stage. Here define $x = (x_1, \ldots, x_k)$ as a vector of chemical inputs such as fungicides, miticides, insecticides, etc.

After the growing season the grower realizes the outcomes of hop yield y and pesticide residue q at the end of this stage. Here q is interpreted as the level of pesticide residue (inversely related to quality). Terms related to hop quality are often specified in a contract (Note 2).

In the marketing stage, the hop buyer/importer decides whether to accept or to reject the contracted hops. We assume the buyer/importer will accept the hops only when the pesticide residue is below a specified tolerance level $q < \overline{q}$. Otherwise the buyer/importer rejects the hops delivery.

2.2 Pesticide Residue and the MRL

For the purpose of theoretical analysis, we assume hop yield, $y \in [0, a]$, is stochastic. Let $q \in [0, b]$ be the pesticide residue which is also stochastic. Define a conditional joint probability density function as:

$$f(y, q \mid x) \tag{1}$$

where,

x is the vector of chemical inputs. This distribution is taken to be realized at the end of the production stage. In a general sense this function structures the relationship among chemical use, crop yield, and residue. More specific functional relationships are defined in the simulation section.

A pesticide tolerance level in the form of a maximum residue limit, or MRL, $\overline{q}$, is exogenously determined by a third party such as the government or an importing agent. From a purely statistical perspective, identifying a MRL is equivalent to estimating an extreme percentile of an unknown distribution (MacLachlan & Hamilton, 2010). In this manner one can have a pre-specified confidence that an estimate exceeds the true percentile.

2.3 Input Decisions under Risk

We assume a hop grower makes input decision at the beginning of production stage. If hops are accepted and marketed, i.e., $q < \overline{q}$, growers will receive a higher contracted price $\overline{p}$ and, hence, a higher profits π_1. In this case the grower will receive deterministic revenue of $\overline{p} \cdot \overline{y}$ by fulfilling the contract. If hops are not accepted by the buyer nor marketed, i.e., $q \geq \overline{q}$, the grower will receive a lower price $\hat{p} < \overline{p}$ and, hence, lower profit $\pi_2 < \pi_1$ (Note 3). Combining revenue with costs defines the growers profit function:

$$\begin{aligned} \pi_1 &= \overline{p} \cdot \overline{y} - w \cdot x - \gamma, \quad q < \overline{q} \\ \pi_2 &= \hat{p} \cdot \overline{y} - w \cdot x - \gamma, \quad q \geq \overline{q} . \end{aligned} \tag{2}$$

Here,

$w \cdot x$ is the growers marginal cost of pesticide use and γ represents the remaining production costs.

The grower chooses the chemical input under the joint distribution in Equation (1) and solves the following optimality problem:

$$\max_x V(\pi) = \max_x \int_0^a \int_0^{\overline{q}} u(\pi_1) f(y, q \mid x)\, dq dy + \int_0^a \int_{\overline{q}}^b u(\pi_2) f(y, q \mid x)\, dq dy \tag{3}$$

where the hop grower's risk preferences are represented by the von Neumann-Morgenstern utility function $u(\cdot)$. Risk aversion is assessed using the Arrow-Pratt absolute risk aversion coefficient $r \equiv -\left(\partial^2 U / \partial^2 \pi\right) / \left(\partial U / \partial \pi\right)$, with $r > 0$ representing risk aversion (Pratt, 1964). For a constant r it is known as constant absolute risk aversion.

The optimal level of chemical input solves the first order condition (FOC):

$$\int_0^a\int_0^{\overline{q}} u(\pi_1)\frac{\partial f(y,q\mid x)}{\partial x}dqdy+\int_0^a\int_{\overline{q}}^b u(\pi_2)\frac{\partial f(y,q\mid x)}{\partial x}dqdy$$
$$-w\cdot\left(\int_0^a\int_0^{\overline{q}} u'(\pi_1)f(y,q\mid x)dqdy+\int_0^a\int_{\overline{q}}^b u'(\pi_2)f(y,q\mid x)dqdy\right)=0. \tag{4}$$

The first line in Equation (4) is the marginal effect of chemical input on the distribution of yield and pesticide residue. The second line is the marginal effect of chemical input on the two different utility levels. As shown in Babcock and Hennessy (1996), Falco and Chavas (2009) and Antle (2010), we would expect an increase in input level to change the shape of the distribution. In general, we expect the mean of pesticide residue distribution increases with chemical input. However, the variance effect of an addition chemical input is ambiguous. Thus we cannot rule out that an increase in the chemical input may increase the probability of acceptance and decrease the probability of rejection, or an increase in the chemical input increases the probability of both acceptance and rejection.

If we assume y and q are independent with marginal distributions of $g(y\mid x)$ and $h(q\mid x)$. Then the effect of x on the joint distribution

$$\frac{\partial f(y,q\mid x)}{\partial x}=\left(\frac{\partial g(y\mid x)}{\partial x}h(q\mid x)+\frac{\partial h(q\mid x)}{\partial x}g(y\mid x)\right),$$

can be decomposed into the effects on the marginal distributions. The FOC becomes

$$\int_0^a\int_0^{\overline{q}} u(\pi_1)\left(\frac{\partial g(y\mid x)}{\partial x}h(q\mid x)+\frac{\partial h(q\mid x)}{\partial x}g(y\mid x)\right)dqdy$$
$$+\int_0^a\int_{\overline{q}}^b u(\pi_2)\left(\frac{\partial g(y\mid x)}{\partial x}h(q\mid x)+\frac{\partial h(q\mid x)}{\partial x}g(y\mid x)\right)dqdy$$
$$-w\cdot\left(\int_0^a\int_0^{\overline{q}} u'(\pi_1)g(y\mid x)h(q\mid x)dqdy+\int_0^a\int_{\overline{q}}^b u'(\pi_2)g(y\mid x)h(q\mid x)dqdy\right)=0. \tag{5}$$

Consider the case when $\overline{q}=0$, i.e., the MRL stipulates absolutely no tolerance for pesticide residue. In this case selected terms in the integration of the first line and the third line become zero in Equation (5) and the FOC reduces to

$$\int_0^a\int_0^b u(\pi_2)\cdot\left(\frac{\partial g(y\mid x)}{\partial x}\cdot h(q\mid x)+\frac{\partial h(q\mid x)}{\partial x}\cdot g(y\mid x)\right)dqdy$$
$$-w\cdot\int_0^a\int_0^b u'(\pi_2)\cdot g(y\mid x)\cdot h(q\mid x)dqdy=0. \tag{6}$$

Because the MRL is sufficiently stringent, the optimal rate of chemical inputs is the one that maximizes expected utility from π_2. In addition when hop yield and residue are independent, the effect of the pesticide breaks down into the effect on each marginal distribution.

Now consider the comparative static effect when $\overline{q}>0$. Applying Leibniz's rule yields

$$\frac{\partial x}{\partial \overline{q}}=-\Delta^{-1}\cdot\left[u(\pi_1)\left(\int_0^a h(\overline{q})\frac{\partial g(y)}{\partial x}dy+\int_0^a\frac{\partial h(\overline{q})}{\partial x}g(y)dy\right)\right.$$
$$-\left(\int_0^a u(\hat{\pi}_2)h(\overline{q})\frac{\partial g(y)}{\partial x}dy+\int_0^a u(\hat{\pi}_2)\frac{\partial h(\overline{q})}{\partial x}g(y)dy\right)$$
$$\left.-w\cdot\int_0^a\left(u'(\pi_1)-u'(\hat{\pi}_2)\right)\cdot h(\overline{q})\cdot g(y)dy\right]. \tag{7}$$

In Equation (7) $\pi_1=\overline{p}\cdot\overline{y}-w\cdot x$, $\hat{\pi}_2=\hat{p}(\overline{q})\cdot y-w\cdot x$ is the profit when $q=\overline{q}$. The second order condition $\Delta=\partial^2V/\partial x^2$ is assumed to be negative. A positive sign in Equation (7) would mean a more stringent government MRL provides incentives for chemical reduction. However, the sign on Equation (7) is ambiguous.

3. Materials and Methods

3.1 Hops Survey and Data

A survey was carried out of hop growers' production and management practices. The survey which was conducted in 2012 targeted the population of hop growers in Pacific Northwest (Note 4). The response rate is 8.75% and it covers about 10% of the hop hectares in the Pacific Northwest.

Table 1 provides descriptive statistics for selected variables from the survey data. The average yield per hectare was 2401 kg with average revenue of \$18061/ha. The average contract price was \$7.99/kg with a minimum of \$4/kg and maximum of \$15/kg. The average contract length was 3 years with a minimum less than 1 year and maximum of 5 years.

Table 1. Descriptive statistics for selected variables from the 2012 grower survey

Variable	Mean	Standard Deviation	Minimum	Maximum	N
Yield (kg/ha)	2401.94	656.07	927.72	3801.44	46
Revenue ($/ha)	$18061.09	$6334.08	$9622.25	$37721.05	46
Contract (years)	2.74	1.48	0	5	46
Parcel (hectare)	32.20	33.17	0.20	122.22	46
Price ($/kg)	7.99	3.30	4.41	15.44	46

Note. The value of 0 for contract length was one organic field. A parcel is in hectares reported across all varieties and across all farms.

Other descriptive statistics were reported but not presented in the Table 1. Twenty different hop varieties were grown with Columbus/Tomahawk (20%), Cascade (11%), and Zeus (10%) leading the varieties reported. Growers contracted crops with different agents, including hop merchants (67%), large brewers (31%), and others (2%). None of the growers described themselves as an "organic" grower but one did grow a three hectare parcel of organic hops under a very short term contract (< 1 year). Average yield loss estimated by growers to powdery mildew (2.71%), downy mildew (2.43%) and spider mites (1.14%) which totaled 6.3% with a maximum of 18% and minimum of 0% across growers. On average chemicals were sprayed 6-7 times per season to control powdery mildew, downy mildew and spider mites, in line with other pesticide survey data (Sherman & Gent, 2014). Revenue, costs, and other outcomes were consistent with Galinato et al. (2011).

3.2 Simulation Procedures and Assumptions

To complement our theoretical model, we conduct an illustrative simulation study of hops production and chemical use calibrated to grower survey data. To establish a baseline we simulate expected utility under yield risk with no MRL restrictions ($q < \overline{q}$):

$$EU\left(X = x\right) = \frac{1}{N}\sum_{i=1}^{N} U\left(\pi_{1i}\right) \tag{8}$$

Next we focus, in particular, on simulating the effects of yield risk, risk attitudes and uncertainties of MRLs on input choices. The expectation functional form of Equation (3) is specified as,

$$EU\left(X = x\right) = \frac{N_1}{N}\sum_{i=1}^{N_1} U\left(\pi_{1i}\right) + \frac{N_2}{N}\sum_{i=1}^{N_2} U\left(\pi_{2i}\right) \tag{9}$$

where the first summation is taken over the observations when the MRL is met, $q < \overline{q}$, and the second summation is taken over the observations when the MRL is exceeded, $q < \overline{q}$. The rate of inputs that result in the highest value of Equation (9) is taken to be the expected utility maximizing rate. Similar to Babcock and Hennessey (1996) we select a constant absolute risk aversion (CARA) utility function (Pratt, 1964) as $\mu(\pi;r) = 1 - \exp(-r\pi)$ with r as the coefficient of absolute risk aversion.

A hypothetical yield function is specified dependent upon the number of chemical applications is defined by $y_i = \alpha + \beta x_i - \phi x_i^2$ $(\alpha = 1000, \beta = 2000, \phi = 250)$ where the parameters are calibrated to an illustrative yield profile. When the MRL is not binding the optimal level of chemical is 6 applications, which is close to the mean number of applications reported in the grower survey. A damage function (Damage Profile 1) that reduces yield is initially defined to be symmetric across choices of chemical inputs contingent on responses from the grower survey (scenarios 1-15). Damage Profile 1 considers 4, 5, 6, 7, and 8 applications of chemicals that reduce yield by 10%, 5%, 0%, 5%, and 10% respectively. Variations of this damage profile are examined below in further model scenarios.

Pesticide residue is assumed to be positively correlated with chemical use. MacLachlan and Hamilton (2010) report distributions of pesticide residues are often unknown, and studies have used normal, log normal, Weibull, exponential, or power distributions. In the simulations below the residue is assumed to be distributed in the family of extreme value distributions. Given the outcomes, the hypothetical binding levels of the MRL used in the analysis are 0.4 and 0.2. The exact level of MRL will depend upon the chemical used, time since application, and agents determining its level. Sensitivity analysis is used to examine model outcomes to deviations from the parameter assumptions.

A Monte Carlo simulation is completed to generate data and to realize outcomes from the structure above. Fifty iterations are completed for each simulation scenario with 1000 observations drawn each iteration. The optimal level of chemical use is defined when the expected utility achieves a maximum over a range of choices.

3.3 Scenarios

Scenarios are setup beginning with a baseline model (Scenario 1) and variations of it to provide sensitivity analysis to key model parameters and policy variables. The baseline model is simulated when hop yield has mean of 2241 kg/ha with standard deviation σ_y = 567 (see Table 2). The MRL is not binding and the hop grower exhibits risk neutrality ($r = 0.00001$). Given responses from the grower survey the contract price, $\overline{p}$, is chosen to be \$11/kg. The contract size, $\overline{y}$, is 2241 kg/ha. The hop side agreement price, $\hat{p}$, is \$6/kg.

Table 2. Primitive parameters used to calibrate the baseline model

$\overline{p}$	Hop base price (\$/kg)	11.03	Chosen based on the contract
$\overline{y}$	Contract size (kg/ha)	2241.19	Chosen based on the contract
$\hat{p}$	Hop spot market price (\$/kg)	6.62	A average price based on USDA estimates
y_{mean}	The mean of hop yield (kg/ha)	2241.19	Chosen based on the survey data
σ_y	Standard deviation	567	Chosen based on the survey data
r	Coefficient of risk aversion	0.00001	Chosen to represent risk neutrality

4. Results

Model results for scenarios 1-15 are presented in Table 3, which are deviations from the baseline model. For the baseline model the optimal level of chemical applications is 6 with expected profit of \$4843.30. Scenarios 2 and 3 introduce a binding MRL of 0.4 and 0.2, respectively. Profit reduces to \$3573.87 for Scenario 2 and \$2806.34 for Scenario 3 with the number of chemical applications remaining at 6 for Scenario 2 but decreasing to 5 for Scenario 3. Scenarios 4 and 5 introduce a risk aversion coefficient of 0.02 but the results are nearly identical to Scenarios 2 and 3.

Table 3. Simulation results for risk averse and risk neutral growers producing hops

Scenario	Absolute Risk Aversion (r)	Optimal Chemical Usage (x^c) Expected Utility	Optimal Chemical Usage (x^c) Expected Profit	Expected Profit ($/ha)	Standard Deviation	MRL
1-Baseline	0.00001	6.000	6.000	4843.30	σ_y, σ_{res}	Not Binding
2	0.00001	5.960	6.000	3573.87	σ_y, σ_{res}	0.4
3	0.00001	5.000	5.100	2806.34	σ_y, σ_{res}	0.2
4	0.02	5.960	6.000	3349.12	σ_y, σ_{res}	0.4
5	0.02	5.000	5.080	2672.47	σ_y, σ_{res}	0.2
6	2.0	5.020	6.000	3390.72	σ_y, σ_{res}	0.4
7	2.0	4.740	5.180	2700.95	σ_y, σ_{res}	0.2
8	0.02	6.000	6.000	2901.68	$4\sigma_y, \sigma_{res}$	0.4
9	0.02	5.840	5.120	2483.50	$4\sigma_y, \sigma_{res}$	0.2
10	2.0	4.200	6.000	3592.08	$.5\sigma_y, \sigma_{res}$	0.4
11	2.0	4.000	5.140	3165.65	$.5\sigma_y, \sigma_{res}$	0.2
12	2.0	4.440	5.160	2901.52	$\sigma_y, 2\sigma_{res}$	0.4
13	2.0	4.340	4.860	1576.88	$\sigma_y, 2\sigma_{res}$	0.2
14	2.0	4.000	5.1600	2464.09	$.5\sigma_y, 2\sigma_{res}$	0.4
15	2.0	4.000	4.760	1586.15	$.5\sigma_y, 2\sigma_{res}$	0.2

Scenarios 6 and 7 introduce a larger risk aversion coefficient of 0.20. For Scenario 6, under the MRL = 0.40, the number of chemical applications is reduced to nearly 5 for the risk averse grower and remain at 6 for the risk neutral grower. Under the MRL = 0.20, or Scenario 7, the number of chemical applications is reduced to 4.74 for the risk averse grower and 5.14 for the risk neutral grower. This demonstrates that under certain circumstances the risk averse grower will reduce the number of chemical applications and use fewer chemical applications than the risk neutral grower.

Additional simulations are examined to explore sensitivity of the above results to specifications of the yield and pesticide residue distributions. For scenarios 8 and 9 we inflate the standard deviation of yield by a factor of 4. Under the MRL = 0.40, or Scenario 8, the number of chemical applications is the same as the baseline. However, when the decreases to MRL = 0.2 the number of applications is 5.84 for the risk averse grower and 5.12 for the risk neutral grower. The important observation is that increased riskiness in yield can overshadow restrictions from the MRL, and the number of chemical applications is greater under risk aversion than risk neutrality. For scenarios 10 and 11 we deflate the standard deviation of yield by a factor of 0.5. The opposite is observed in that chemical applications are again now less for the risk averse grower.

Under Scenarios 12 and 13 the standard deviation of the pesticide residue is multiplied by a factor of 2.0, increasing its uncertainty. It is anticipated that increasing the uncertainty of the residue would further decrease the number of chemical applications. For Scenario 12, the number of applications go from about 5 (Scenario 6) to 4.44 under risk aversion. For Scenario 13, the number of applications go from about 4.74 (Scenario 6) to 4.34 under risk aversion. In effect, all else equal, the more growers are uncertain about the pesticide residue the fewer chemical applications will be applied. Finally, Scenarios 14 and 15 further demonstrates as yield risk decreases and variance of the pesticide residue increases then the number of chemical applications decrease.

These results provide several important observations worth discussing. First, all else equal, a binding MRL decreases chemical applications. Second, all else equal, increasing the variance associated with the pesticide residue further decreases the number of chemical applications. However, there is an important balancing act for the grower. As demonstrated above, the riskiness of yield and variance of the residue tradeoff with one another provided an interesting but not clear cut outcomes to guide chemical use. Finally, in circumstances where reductions in chemical applications are optimal, there is an opportunity for integrated pest management strategies or, conversely, greater use of other pesticides not subject to the MRL.

4.1 Alternative Damage Profiles

Table 4 presents outcomes from different damage profiles. Initially we considered 4, 5, 6, 7, and 8 applications of chemicals with damages of 10%, 5%, 0%, 5%, and 10%, respectively (Damage Profile 1). Damage Profile 2 for 4, 5, 6, 7, and 8 applications of chemicals are damages of 50%, 25%, 0%, 25%, and 50%, respectively (Damage Profile 2). There is no difference between outcomes for the Baseline and Scenario 16. Indeed, because of the larger magnitude of damage, even with a MRL = 0.20 (Scenario 17), there is no discernible difference in chemical applications relative to the baseline.

Table 4. Further simulation results under alternative damage profiles

Scenario	Damage Profile	Absolute Risk Aversion (r)	Optimal Chemical Usage (x^c) Expected Utility	Optimal Chemical Usage (x^c) Expected Profit	Expected Profit ($/ha)	MRL
1-Baseline	1	0.00001	6.000	6.000	4843.30	Not Binding
16	2	0.00001	6.000	6.000	5225.90	Not Binding
17	2	2.0	5.920	6.000	2978.31	0.2
18	3	0.00001	7.000	7.000	4824.44	Not Binding
19	3	2.0	4.560	5.000	3340.17	0.2

Now consider an asymmetric profile with damages of 10%, 5%, 2.5%, 0%, and 5%, respectively (Damage Profile 3). Scenario 18 with no binding MRL simply increases the number of applications from 6 to 7. This is not surprising with the shift in yield from the asymmetric damage profile. Imposing a MRL = 0.20 in Scenario 19 reduces the number of applications to 4.56 for the risk averse grower and 5.00 for the risk neutral grower. This is consistent with Scenario 7 but exhibits a larger decrease in the number of applications. Under this profile more applications of chemicals control better yield damage but also increase chemical residue. It is clear from the above scenarios that the likelihood and magnitude of change will depend on various factors including the shape of the yield and damage functions.

5. Conclusion

Many forces affect a grower's chemical input usage during the hop production season and marketing process. This paper focuses on how pesticide residue and yield risk affect a hop grower's chemical input decision. Intuitively, it is likely that a grower/exporter uses less chemical inputs when he or she is facing more stringent tolerance limits on pesticide residue (i.e., MRLs). But other tradeoffs exist. Consequently, an expected utility model with risk preferences is specified and simulated to identify grower tradeoffs between yield risk and uncertainty in pesticide residue with MRLs. The empirical model illustrates hop production and exports in the Pacific Northwest.

Model results provide several important observations worth discussing. First, all else equal, a binding MRL tend to decrease chemical applications. Second, all else equal, increasing the variance associated with the pesticide residue (more uncertainty) further decreases the number of chemical applications. However, there is an important balancing act for the grower. As demonstrated above, the riskiness of yield and variance of the pesticide residue tradeoff with one another providing and interesting but not clear cut outcomes to guide chemical use. Finally, in circumstances where reductions in chemical applications are optimal, there is an opportunity for integrated pest management strategies or, alternatively, greater use of other pesticides not subject to MRL restrictions.

The model and empirical results are hypothetical and not a definitive study of MRLs in agricultural production. Nevertheless they provide an initial assessment of the situation in hop production and interesting insights to growers' decisions and the consequences of these decisions. Because of limited data we simulate scenarios with average chemical costs and stylized damages. We focused only on yield damage in the present analysis, but reductions in crop quality also impact decisions on pesticide use. Quality defects due to pests may be equally important to yield depression in some instances. However, damage functions for quality defects are difficult to assess and may interact with customer demand (Zadoks, 1985). As a result our findings are general observations, as opposed to specific recommendations. Future research should include gathering more extensive data on yield and quality damage, and the relationship between pesticide use and resultant residue levels. Moreover, it should examine the issue of ambiguity loss as well as risk aversion.

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Notes

Note 1. For example, hops have historically been purchased using multi-year forward production contracts. Only a small share of the hops produced targets the spot market. On average, over 90% of the crop has been contracted in advance of harvest where hop's price and purchase quantity are "locked in" at the time the contract is issued.

Note 2. In general, hop's descriptive quality attributes include hop cone's color, size, moisture etc. In the current paper we are interested in the quality issues related to pesticide residue, which we assume can be tested and determined by the hop merchant.

Note 3. Personal communications with hop growers in the Pacific Northwest indicate that growers often have side agreements with other growers by which they purchase hops to fulfill contracts in deficit events. Hence, we assume for convenience that the contact size is met with a lower net price.

Note 4. The majority of hop farms are located in Washington's Yakima Valley. In 2008 for example, Washington State produced 12381 hectares of hops, which made up about 75% of the US commercial hop's production. Behind Washington was Oregon with 2578 hectares and Idaho with 1592 hectares which make up around 15.5% and 9.5% of the US commercial hop production respectively.