PRODUCTION RISK AND MAXIMUM RESIDUE LIMITS:
A CASE STUDY OF HOPS PRODUCTION

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ABSTRACT

This paper examines how maximum residue limits (MRLs) affect a hop growers' optimal choice of chemical applications to control pests and diseases. All else equal, decreases in the MRL tend to induce risk averse growers to apply fewer chemicals than risk neutral growers. In reality, growers must balance both yield risk and uncertainty in MRLs when making chemical application decisions. To empirically address these issues we specify an expected utility model calibrated to data collected from a 2012 survey of hop growers in the Pacific Northwest and then simulate hop grower decisions across a myriad of scenarios. As anticipated, risk preferences contribute to explaining higher chemical use. Under certain circumstances risk preferences coupled with uncertainty underlying MRLs have the potential to tip the decision towards less chemical uses with potential for more growers implementing integrated pest management strategies.

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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 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 and Zilberman, 1983; Babcock and Hennessy, 1996). In contrast this article develops a model of a grower's input decisions under yield risk with uncertainty in MRLs. We specify a model that (i) incorporates the grower's risk preferences; (ii) emphasizes the role of MRLs under forward hop contracts;[1] (iii) proposes a decision rule that balances both yield risk and uncertainties of MRL. The model is calibrated consistent with hop production in the Pacific Northwest. A wide range of scenarios are simulated to assess hop grower response to key production, trade and policy parameters.

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 paper makes several primary contributions not present in the literature. First, it demonstrates tradeoffs that growers balance between yield risk and uncertainty of MRLs 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 growers previously not available.

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[1] Hops have historically been purchased using multi-year forward production contracts. Only a small share of the hops produced targeting 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.

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. Results and implications are then provided. We end with concluding remarks and discussion future directions for research.

2. Theoretical Model

2.1. Hop Production and Marketing Process

Figure 1 presents a stylized hop production and marketing timeline. 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 ($\bar{p}$), size of contract (i.e. purchase quantity) ($\bar{y}$), and the pesticide tolerance level ($\bar{q}$).

Given a hop contract, the representative hop grower makes decision on the choice of chemical levels at the beginning of the production stage. $x = (x_1, ..., x_k)$ is a vector of chemical inputs such as fungicides, miticides, insecticides, etc.

Production starts and the grower realizes the outcomes of hop yield y and pesticide residue q at the end of this stage.[2] Here q is interpreted as the quality represented with focus on the level of pesticide residue. This is because terms related to hop quality in a contract are often specified with respect to the quantity of pesticides residues.

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[2] In general, we are interested in the hop's descriptive quality attributes such as 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. Therefore, q is a variable of hop's quality which reflects the quantity of pesticides residue.

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

2.2. Pesticide Residue and the MRL

For the purpose of theoretical analysis, we assume hop yield, y, is nonstochastic. On the other side, $q \in [0, \ell]$ is the pesticide residue as the stochastic output from the production. We assume it distributed according to conditional probability density function $f(q \mid x)$ where x is the input. This distribution is taken to be realized at the end of the production stage.

A pesticide tolerance level or maximum residue limit (MRL) is defined as a scalar $\bar{q}$, which is exogenously determined by a third party such as the government or an importing agent.[3] If $q \le \bar{q}$, the grower receives the nonstochastic contract price $\bar{p}$. If $q > \bar{q}$, the grower will receive some second price (price from the side agreement) $\hat{p}(\bar{q})$, where $\hat{p}'(\bar{q}) > 0$. We further assume $\bar{p} > \hat{p}(\bar{q})$, i.e., a grower will receive higher profits (i.e., prices) if hops are successfully sold at the contract price during the marketing stage, where the pesticide residues is below the tolerance level.

2.3. Input Decisions under Risk

We assume a hop grower makes input decision at the beginning of production stage. The damage adjusted yield function is

$$(y \cdot (1 - D(x))), \tag{1}$$

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[3] The value of MRLs for hops depends on the type of chemical.

which is the damage adjusted hop yield surplus (or deficit) that can be marketed through side agreements at the price $\hat{p}(\bar{q})$. If the MRL is exceeded then we assume the reduced price $\hat{p}(\bar{q}) < \bar{p}$ is the firms next best alternative.[4]

To complete the specification, in (1) a damage function, $D(x)$, is specified dependent upon level of chemical inputs, i.e., it represents the proportion of the destructive capacity (damage) of the diseases or insect which is reducing in disease control inputs (Lichtenberg and Zilberman, 1986; Sexton et al., 2007). Therefore $D'(x) < 0$ at an increasing rate $D''(x) > 0$. We assume $D \in [0,1]$ and $\lim_{x \to \infty} D = 0$, which means damage approaches zero as damage control inputs increases infinitely.

If hops are accepted and marketed, i.e., $q < \bar{q}$, growers will receive a higher contracted price $\bar{p}$ and, hence, a higher profits π_1. In this case the grower will receive deterministic revenue of $\bar{p} \cdot \bar{y}$ by fulfilling the contract. If hops are not accepted by the buyer nor marketed, i.e., $q \geq \bar{q}$, the grower will receive a lower price $\hat{p}$ and, hence, lower profit π_2.

Combining revenue with costs defines the growers profit function:

$$\pi_1 = \bar{p} \cdot \bar{y} + \hat{p}(q) \cdot \left(y \cdot \left(1 - D(x)\right) - \bar{y}\right) - w \cdot x - \gamma, q < \bar{q} \tag{2}$$

$$\pi_2 = \hat{p}(\bar{q}) \cdot (y \cdot (1 - D(x))) - w \cdot x - \gamma - \delta \cdot \bar{p} \cdot \bar{y}, q \geq \bar{q}.$$

which accounts for the revenues from both the contract and side agreement minus variable input and other costs. When $q \geq \bar{q}$, it is assumed that the grower must meet contract terms by purchasing marketable hops using a side agreement with another grower and there is a transaction cost of $\delta \cdot \bar{p} \cdot \bar{y}$. The input price vector for chemicals is w and γ represents the

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[4] 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.

remaining production costs. In the state when pesticide residue meets the MRL, the grower derives the expected utility from the profit π_1; in the state when the pesticide residue exceed the MRL, the grower derives expected utility from the lower profit π_2 from side agreement.

The grower chooses the chemical input which solves the following optimality problem:

$$\max_x V(\pi) = \max_x \int_a^{\bar{q}} u(\pi_1) f(q \mid x) dq + \int_{\bar{q}}^{b} u(\pi_2) f(q \mid x) dq. \tag{3}$$

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 (CARA).

For convenience we assume $D(x) = 0$, i.e., the damage is 0%. Hence growers choose inputs such that there is no yield loss from diseases or pests. We conduct sensitive analysis with respect to different damage profile in the following empirical section and compare the optimal levels of chemical usage.

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

$$\begin{aligned} &\int_a^{\bar{q}} u(\pi_1) \frac{\partial f(q \mid x)}{\partial x} dq + \int_{\bar{q}}^{b} u(\pi_2) \frac{\partial f(q \mid x)}{\partial x} dq \\ &- w \cdot \left(\int_a^{\bar{q}} u'(\pi_1) f(q \mid x) dq + \int_{\bar{q}}^{b} u'(\pi_2) f(q \mid x) dq \right) = 0. \end{aligned} \tag{4}$$

The first line in (4) is the marginal effect of chemical input on the distribution of pesticide residue. 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 the probabilities 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. The second line is the marginal effect of chemical input on the utility. The second order condition is assumed to be negative, $\rho = \partial^2 V / \partial x^2 < 0$. [5]

Of interest is when growers are risk averse, under what condition does a decrease in MRL, i.e. a more stringent MRL, decreases the optimal chemical input? A decrease in chemical input may increase the probability that hops are accepted where the pesticide residue meets the MRL, thus reduces the risk of rejection. On the other hand, a decrease in chemical input also increases the production risk of pest infestation. For a risk averse hop grower, a more stringent MRL decreases the optimal chemical input only if the first effect dominates.

We see this by doing the comparative statics from (4). By Leibniz's rule:

$$\frac{\partial x}{\partial \bar{q}} = -\rho^{-1}\left[\int_{\bar{q}}^{b} u'(\pi_2)\cdot \hat{p}'(\bar{q})\cdot y \cdot \frac{\partial f(q \mid x)}{\partial x} dq - w \cdot \int_{\bar{q}}^{b} u''(\pi_2)\cdot \hat{p}'(\bar{q})\cdot y \cdot f(q \mid x) dq\right] \tag{5}$$

which is

$$\frac{\partial x}{\partial \bar{q}} = -\rho^{-1} \cdot u'(\pi_2)\cdot \hat{p}'(\bar{q})\cdot y \cdot \left(\int_{\bar{q}}^{b} \frac{\partial f(q \mid x)}{\partial x} dq - w \cdot \frac{u''(\pi_2)}{u'(\pi_2)} \int_{\bar{q}}^{b} f(q \mid x) dq \right) \tag{6}$$

In the bracket of (6) $u''(\cdot)/u'(\cdot) = -r < 0$ is the negative of coefficient of risk aversion. Since $\hat{p}'(\bar{q}) > 0$, the product of the terms outside the brackets in (6) is positive. The third term in the bracket is negative. Therefore the sign of (6) is ambiguous. The first term represents the marginal effect of chemical on the probability of rejection. A positive sign implies an increase in chemical input increases the probability of rejection; a negative sign implies an increase in

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[5] The necessary condition for the negative second order condition is $\frac{\partial f(q \mid x)}{\partial x} > 0$, and $\frac{\partial^2 f(q \mid x)}{\partial x^2} < 0$.

chemical input decreases the probability of rejection. The second term represents the marginal effect of chemical input on the damage control. If an increase in chemical input increases the probability of rejection, and this effect dominates all other effects, a decrease in MRLs decreases the optimal level of chemical input.

3. Hops Survey and Data

A survey was carried out of hop grower's production and management practices. The survey which was conducted in 2012 targeted the population of hop growers in Pacific Northwest.[6] The response rate is 8.75% and it covers about 10% of the hop acreage in the Pacific Northwest.

Table 1 provides descriptive statistics for selected variables from the survey data. The average yield per acre was 2143 pounds with average revenue of $7,309/acre. The average contract price was $3.63/pound with a minimum of $2/pound and maximum of $7/pound. The average contract length was 3 years with a minimum less than 1 year and maximum of 5 years.

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 in acreage. 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 an eight acre 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

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[6] The majority of hop farms are located in Washington's Yakima Valley. In 2008 for example, Washington State produced 30,595 acres of hops, which made up about 75% of the US commercial hop's production. Behind Washington was Oregon with 6370 acres and Idaho with 3933 acres which make up around 15.5% and 9.5% of the US commercial hop production respectively.

season to control powdery mildew, downy mildew and spider mites. Revenue, costs, and other outcomes were consistent with Galinato et al., (2011).

4. Simulation Procedures and Assumptions

To complement our theoretical model, we conduct a simulation study of hops production and chemical use calibrated to the grower survey data. To establish a baseline we simulate expected utility under yield risk but with no uncertainty or MRL restrictions ($\tilde{p} = \bar{p}$):

$$EU(X = x) = \frac{1}{N}\sum_{i=1}^{N} U(\pi_{1i}) \tag{7}$$

Here the growers profit is defined as $\pi_1 = \bar{p} \cdot \bar{y} + \hat{p}(q) \cdot (y - (1 - D(x)) - \bar{y}) - w \cdot x - \gamma$.

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 (3) is specified as,

$$EU(X = x) = \frac{N_1}{N}\sum_{i=1}^{N_1} U(\pi_{1i}) + \frac{N_2}{N}\sum_{i=1}^{N_2} U(\pi_{2i}) \tag{8}$$

where the first summation is taken over the observations when the MRL is met, $q < \bar{q}$, and the second summation is taken over the observations when the MRL is exceeded, $q \geq \bar{q}$. The rate of inputs that result in the highest value of (8) 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 $u(\pi; r) = 1 - \exp(-r\pi)$ with r as the coefficient of absolute risk aversion.

The damage function is initially defined to be symmetric across choices of chemical inputs contingent on responses from the grower survey. If the MRL is not binding the optimal level of chemical is 6 applications, which is close the mean number of applications reported by growers. Initially we assume consider 4, 5, 6, 7, and 8 applications of chemicals with damages of 10%, 5%, 0%, 5%, and 10% respectively. Variations of this damage profile are examined below in further model scenarios.

The MRL is assumed to be positively correlated with chemical use. It is assumed to be distributed in the family of extreme value distributions and it is calibrated in the model. MacLachlan and Hamilton (2010) report distributions of MRL are often unknown, and studies have used normal, log normal, Weibull, exponential, or power distributions. Sensitivity analysis is used to examine model outcomes to deviations from the parameter assumptions. The exact level of MRL will depend upon the chemical used, time since application, and agents determining its level.

4.1. 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 2000 pounds/acre with standard deviation $\sigma_y = 567$ (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, $\bar{p}$, is chosen to be \$5/pound. The contract size, $\bar{y}$, is 2000 pound/acre. The hop side agreement price, $\hat{p}$, is \$3/pound. The optimal level of chemical use is defined when the expected utility achieves a maximum over a range of choices.

5. 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 $1,960.05. Scenarios 2 and 3 introduce a binding MRL of 0.4 and 0.2, respectively. Profit reduces to $1,446.32 for Scenario 2 and $1135.71 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.

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 MRL 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=0.02 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 overshadows uncertainty in 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 MRL is multiplied by a factor of 2.0, increasing its uncertainty. It is anticipated that increasing the uncertainty of the MRL 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 MRL the fewer chemical applications will be applied. Finally, Scenarios 14 and 15 further demonstrates as yield risk decreases and uncertainty of the MRL increases then the number of chemical applications decrease.

There results provide several important observations worth discussing. First, all else equal, a binding MRL decreases chemical applications. Second, all else equal, increasing the uncertainty associated with the MRL 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 uncertainty of the MRL 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.

5.1. 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.

Now consider an asymmetric profile wherein 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.

6. Conclusion

Many forces during the hop production and marketing process affect a grower's chemical input usage. This paper focuses on how uncertainty of MRLs and yield risk affect a hop grower's chemical input decision. Intuitively, it is likely that grower is more willing to use less of chemical inputs when he or she is facing a regulation on hop's quality, such as tolerance limit on pesticide residue.

An expected utility model with risk preferences is used to identify grower tradeoffs for chemical use decisions. The model is calibrated to hop production in the Pacific Northwest.

Model results provide several important observations worth discussing. First, all else equal, a binding MRL decreases chemical applications. Second, all else equal, increasing the uncertainty associated with the MRL 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 uncertainty of the MRL 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.

The model and empirical results are not a definitive study of MRLs in agricultural production, but rather provide an initial assessment of situation in hop production. Because of limited data we simulate scenarios with average chemical costs and stylized damages. As a result our findings are general observations, as opposed to specific recommendations. Future research should include gathering more extensive data on damage and MRLs. Moreover, it should examine the issue of ambiguity loss as well as risk aversion.

7. Conflict of Interests

The authors declare that there is no conflict of interests regarding the publication of this article.

TABLE 1. Descriptive Statistics for Selected Variables from the 2012 Grower Survey

Variable	Mean	Standard Deviation	Minimum	Maximum	N
Yield (pounds/acre)	2143.45	585.46	827.88	3392.33	46
Revenue ($/acre)	$7,309.22	$2,563.37	$3,894.07	$15,265.50	46
Contract (years)	2.74	1.48	0	5	46
Parcel (acres)	79.58	81.97	0.5	302	46
Price ($/pound)	3.63	1.50	2.00	7.00	46

The value of 0 for contract length was one organic field.

A parcel is acreage reported across all varieties and across all farms.

TABLE 2. Primitive Parameters Used to Calibrate the Baseline Model

$\bar{p}$	hop base price (dollar/pound)	5	Chosen based on the contract
$\bar{y}$	contract size (pounds/acre)	2000	Chosen based on the contract
$\hat{p}$	hop spot market price (dollar/pound)	3	the average price USDA
y_{mean}	the mean of hop yield (pounds/acre)	2000	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

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 ($/acre)	Standard Deviation	MRL
1-Baseline	0.00001	6.000	6.000	1960.0544	σ_y, σ_{MRL}	Not Binding
2	0.00001	5.960	6.000	1446.3231	σ_y, σ_{MRL}	0.4
3	0.00001	5.000	5.100	1135.7080	σ_y, σ_{MRL}	0.2
4	0.02	5.960	6.000	1355.3702	σ_y, σ_{MRL}	0.4
5	0.02	5.000	5.080	1081.5309	σ_y, σ_{MRL}	0.2
6	2.0	5.020	6.000	1372.2042	σ_y, σ_{MRL}	0.4
7	2.0	4.740	5.180	1093.0576	σ_y, σ_{MRL}	0.2
8	0.02	6.000	6.000	1174.2915	$4\sigma_y, \sigma_{MRL}$	0.4
9	0.02	5.840	5.120	1005.0588	$4\sigma_y, \sigma_{MRL}$	0.2
10	2.0	4.200	6.000	1453.6929	$.5\sigma_y, \sigma_{MRL}$	0.4
11	2.0	4.000	5.140	1281.1181	$.5\sigma_y, \sigma_{MRL}$	0.2
12	2.0	4.440	5.160	1174.2261	$\sigma_y, 2\sigma_{MRL}$	0.4
13	2.0	4.340	4.860	638.1528	$\sigma_y, 2\sigma_{MRL}$	0.2
14	2.0	4.000	5.1600	997.2045	$.5\sigma_y, 2\sigma_{MRL}$	0.4
15	2.0	4.000	4.760	641.9051	$.5\sigma_y, 2\sigma_{MRL}$	0.2

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 ($/acre)	MRL
1-Baseline	1	0.00001	6.000	6.000	1960.0544	Not Binding
16	2	0.00001	6.000	6.000	2114.8921	Not Binding
17	2	2.0	5.920	6.000	1205.3042	0.2
18	3	0.00001	7.000	7.000	1952.4202	Not Binding
19	3	2.0	4.560	5.000	1351.7469	0.2

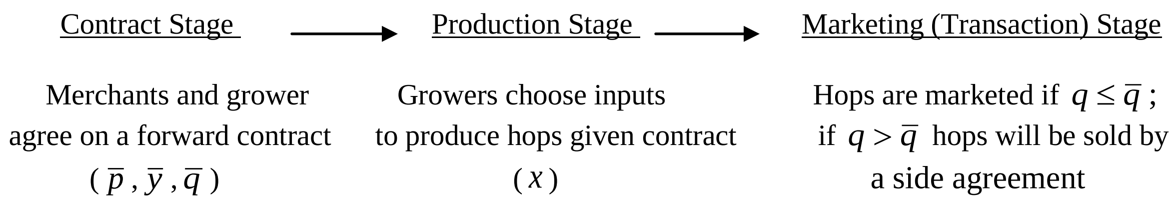

Figure 1. Hop Production and Marketing Process

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