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By

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Abstract

Biofuels, as alternative transportation fuels, are now being used globally. Taking advantage of in-state feedstock supply is an efficient way to stimulate in-state biofuel industries and the local economy. This paper uses several models to estimate supply equations for major biofuel feedstock crops in Washington. We estimate expected utility maximization models, expected profit maximization models, and several pragmatic models. We examine the comparative statics results of the models, and use the results to draw important implications for Washington policy makers and for farmers who are considering production of biofuel feedstocks.

Keywords: biofuel feedstock, output uncertainty, price uncertainty, profit maximization, supply

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Washington Biofuel Feedstock Crop Supply Analysis

Biofuels, as alternative transportation fuels derived from biomass, are now being used globally. Biofuels can provide local economic benefits such as additional markets for farm crops and additional jobs in rural communities. Broader benefits include potential mitigation of greenhouse gas emissions (under certain scenarios) as well as improvements in energy security by decreasing dependence on foreign sources of fuels.

Biofuel production and use are in their infancy but are experiencing a period of rapid growth. New markets are being created to help foster biofuel growth across the United States. Washington State's push toward biofuels is evidenced by state and local government mandates, expansion of state-owned vehicles running on biofuels, increases in the number of biofuel plants, and increases in the acreage of feedstocks.

Taking advantage of in-state feedstock supply is an efficient way to stimulate in-state biofuel industries and the local economy. Thus, analyzing the existing feedstock supply and potential in Washington is important. "Under current technology, Washington's potential biofuel crops include corn and sugar beets for sugar-based ethanol; oilseed crops (canola, soybeans, camelina, mustard, safflower, sunflower and peanuts) for biodiesel; and poplar, grain straw, switch grass and other fiber sources for cellulosic ethanol." (Yoder et. al., 2007, p. 7)

Corn ethanol is the major biofuel now used in the United States. In Washington, corn is primarily grown under irrigation in the Columbia Basin. It is relatively expensive to grow corn in Washington compared to the Midwest. Although there was a 67% increase in Washington corn harvested acreage in 2007 compared to 2006, it contributes a trivial part of national production (about 1/10 of 1 percent). Sugar beets were a common crop produced in Washington until 1978, but little has been grown since processing facilities were closed due to low sugar prices and high energy costs. The few acres of sugar beets still grown in Washington are near Moses Lake, and research on the economic potential for sugar beets as a biofuel feedstock is necessary and underway.

Compared to their experience in growing grains, oilseed crops are comparatively new to Washington's farmers. Economic viability and agronomic refinements to plant and harvest techniques, nutrient inputs, soil management, and weed and pest control are just beginning (Washington State Biofuels Advisory Committee Report. August 2007). Canola has the highest oil yield of the various oilseed crops and has been grown in limited quantities for several decades in Washington. Mustard and safflower have lower oil yields than canola. Soybeans can be grown in the warmer southern portion of the Columbia Basin but only under irrigation. Camelina, sunflower and peanuts are under cropping trials in the State.

The final type of biofuel feedstock is cellulosic biomass, inedible plants grown on less than optimal farmland. Use of cellulosic feedstock will mitigate the food versus fuel problem but will take time for producers to gain experience to grow and for researchers and processors to innovate with improved technologies to convert cellulose to fuel. We do not consider cellulosic feedstock supplies in this paper.

With more farmers considering production of biofuel feedstocks, an examination of their supply response is critical for purposes of predicting future crop prices as well as food and fuel supplies. The high demand for biofuel production that may or may not persist could drive feedstock prices to be high and variable which will play an important role in farmers' planting decisions. Thus, the analysis of biofuel feedstock supplies must take crop price and output uncertainty into account.

Much research has focused on crop supplies. Some studies have incorporated output price or quantity risk into the economic models of supply. This paper develops several models under utility maximization considering output and/or price uncertainty or under profit maximization without risk to examine the supply of major biofuel feedstocks in Washington. Its purpose is to predict supply response and guide Washington farmers in making optimal production decisions as the biofuel industry develops in the State. Our objectives are to (a) estimate supply equations for major biofuel feedstock crops, (b) examine the comparative statics results of the models, and (c) use the results to draw important decision-making implications for Washington farmers who are considering production of biofuel feedstock crops.

Relevant Literature

The research literature on crop supplies under risk is extensive. We will illustrate the extent of this literature by citing just a few and will give relatively greater emphasis to literature that has addressed both profit and risk motives.

Just (1974) generalized the adaptive expectations geometric lag model by including quadratic lag terms indicative of risk and applied the model to the analysis of California field-crop supply response. Pope (1982) addressed conceptual and estimation issues to develop procedures for incorporating risk into a wide range of production economic models and procedures.

Chavas and Holt (1990) developed an acreage supply response model under expected utility maximization considering price and yield uncertainty using subjective probability distributions and investigated its empirical implications for U.S. corn and soybean acreages. Pope and Just (1991) proposed an econometric test for distinguishing the class of preferences and implemented it for potato supply response in Idaho. Meyers and Robison (1991) extended the theory of the firm facing a random output price to include industry equilibrium conditions and developed an aggregate model under risk which displays the linkages between risk, return and land prices. Coyle (1992) developed tractable dual models of production under risk aversion and price uncertainty within the context of a mean-variance model of utility maximization. Saha, Shumway and Talpaz (1994) used an expo-power utility function to jointly estimate risk preference structure, degree of risk aversion and production technology and implemented it for a sample of Kansas wheat farmers. Chavas and Holt (1996) developed a maximum likelihood procedure to jointly estimate risk preferences and technology under very general conditions and used it to examine U.S. corn-soybean acreage decisions.

Saha and Shumway (1998) derived the complete set of refutable propositions for the competitive firm model under a general wealth structure that encompasses output price and quantity risk as special cases and empirically tested some of the propositions using firm-level data. Adrangi and Raffiee (1999) developed a general model of the competitive firm's behavior under output and factor price uncertainty to evaluate the role of market interdependencies in analyzing long-run equilibrium conditions and the comparative statics of increased uncertainty in output and input prices. Kumbhakar (2002) dealt with specification and joint estimation of risk preferences, production risk, and technical inefficiency. Alghalith (2007) modified and expanded the duality theory and implemented a tractable empirical procedure for estimating supply response and testing hypotheses under both price and output uncertainty.

In this study, we will consider output price and quantity risk motivations in our model of expected utility maximization. We will also consider both risks associated with the feedstock commodity as well as the influence of risks from rotational crops to estimate the optimal supply response. Alternative models will maintain the hypothesis that producers are risk-neutral, profit-maximizing firms. They will be developed and estimated subject to various restrictions implied by profit maximization.

Data

The primary biofuel feedstock crops currently being grown in Washington or being given serious consideration by farmers are corn, sugar beets and canola. State-level annual data for these crops and their primary rotational crops are used in the analysis. We consider three rotational pairs – corn and potatoes, sugar beets and alfalfa hay, canola and wheat. The production data for corn, potatoes and alfalfa hay and the market price data for potatoes and alfalfa hay for Washington from 1960 to 2006 are from the USDA National Agricultural Statistics Service (NASS). The production data for sugar beets, market price data and government program payments for corn and sugar beets, and aggregate input price index data for Washington from 1960 to 2004 were compiled by Eldon Ball (Ball, Hallahan, and Nehring 2004). We extended these data to 2005 and 2006 using USDA NASS price and quantity data and Eldon Ball's tabulation of government program payments.

Since time series data for U.S. and state-level canola production do not exist for this length of time, we use annual data for four states from 1992 to 2004. State-level production, market price, government program payments and aggregate input price index data for canola and wheat for Washington, Idaho, Minnesota and North Dakota are from Eldon Ball.

Public research data for each state for the period 1961-2004 are from Wallace Huffman. These data represent the estimated investment stock values of public research expenditures and were calculated based on a trapezoidal function of past expenditures (Huffman and Evenson 1989). Because the stock of public research investment was nearly constant during the final five years, the stock for 2005 and 2006 was presumed to be the same as for 2004.

Method of Analysis

We estimate supply equations for three pairs of crops commonly grown in rotation in Washington. They include corn and potatoes, sugar beets and alfalfa hay, canola and wheat. We have enough observations for corn, potatoes, sugar beets and alfalfa hay to introduce output price and quantity risk along with profit into an expected utility function. Farmers are expected to be risk averse and maximize the expected utility of profit and uncertainty. We use Model 1 to estimate supply functions accounting for both output price and quantity risks, Model 2 to estimate supply functions under both output price risk and risk-neutral profit maximization, Model 3 to estimate supply functions under risk-neutral profit maximization using panel data, and Model 4 (a set of pragmatic models) to estimate supply functions while maintaining the most important expectation under profit maximization (i.e., that own-price supplies are upward sloping and statistically significant).

Because of limited data for canola, we use panel data and estimate supply equations for canola and wheat based only on risk-neutral profit maximization (Model 3) using a multi-state panel model. We use this model to focus on Washington supply response of canola.

Model 1 – Expected Utility Maximization under Output Price and Quantity Risk

Consider a farmer with two rotational crops. When she is making her planting decisions, she faces uncertain output prices given by $p_i = \overline{p}_i + \sigma_i \varepsilon_i$, where $i = 1,2$ denotes two rotational crops, ε_i is random with $E[\varepsilon_i] = 0$ and $Var[\varepsilon_i] = 1$; thus, $E[p_i] = \overline{p}_i$ and $Var[p_i] = \sigma_i^2$. The output level realized at harvest time is also uncertain due mainly to variability in weather, soil, pests, and disease. We denote output as $q_i = \overline{q}_i + \theta_i \eta_i = y_i + \theta_i \eta_i$, where η_i is random with $E[\eta_i] = 0$ and $Var[\eta_i] = 1$, so that $E[q_i] = \overline{q}_i = y_i$ and $Var[q_i] = \theta_i^2$. Input prices are known with certainty at planting time, and costs are represented by a cost function, $c_i(y_i, w)$, where y_i

is expected output for one crop and w is the state-level aggregate input price. The farmer can estimate individual crop costs at planting from expected crop output level and aggregate input price.

The profit function for this farm manager is:

(1) $$\pi = p_1 q_1 + p_2 q_2 - c_1(y_1, w) - c_2(y_2, w).$$

We assume this farm manager is risk averse and maximizes the expected utility of profit:

(2) $$\underset{y_1, y_2}{Max}\, E[U(\pi)] = E[U(p_1 q_1 + p_2 q_2 - c_1(y_1, w) - c_2(y_2, w))].$$

Assuming that standard regularity conditions apply to the technology, there exist optimal expected output levels y_1^* and y_2^* that maximize profit

$\pi^* = p_1(y_1^* + \theta_1 \eta_1) + p_2(y_2^* + \theta_2 \eta_2) - c_1(y_1^*, w) - c_2(y_2^*, w)$. Thus we can get the indirect expected utility function with profit-maximizing expected output levels:

(3) $$\begin{aligned} &V(\bar{p}_1, \bar{p}_2, \sigma_1, \sigma_2, \theta_1, \theta_2, w) \\ &= E[U(p_1(y_1^* + \theta_1 \eta_1) + p_2(y_2^* + \theta_2 \eta_2) - c_1(y_1^*, w) - c_2(y_2^*, w))]. \end{aligned}$$

Applying the envelope theorem to (3), we obtain the first derivatives of indirect expected utility to expected prices of the crops. For the first crop:

(4) $$\frac{\partial V}{\partial \bar{p}_1} = V_{\bar{p}_1} = y_1^* E[U'(\pi^*)] + \theta_1 E[U'(\pi^*)\eta_1].$$

If there is only price risk, we can derive a supply function directly from (4) since η_1 will be zero in that case. However, with η_1 also a random term representing output uncertainty, we use the second-order Taylor's series expansion to deal with the second term in (4).

Consider an approximation of $U'(\pi^*)$ around the arbitrary point $\hat{\pi}$:

(5) $$U'(\pi^*) \approx U'(\hat{\pi}) + U''(\hat{\pi})(\pi^* - \hat{\pi}).$$

Multiplying both sides of (5) by η_1 and taking expectations, we obtain:

$$
\begin{aligned}
(6)\qquad & E[U'(\pi^*)\eta_1] \approx E[U'(\hat{\pi})\eta_1] + E[U''(\hat{\pi})(\pi^* - \hat{\pi})\eta_1] \\
&= U''(\hat{\pi})E[\pi^*\eta_1] \\
&= U''(\hat{\pi})E[((\bar{p}_1 + \sigma_1\varepsilon_1)(y_1^* + \theta_1\eta_1) + (\bar{p}_2 + \sigma_2\varepsilon_2)(y_2^* + \theta_2\eta_2) - c_1(y_1^*, w) - c_2(y_2^*, w))\eta_1] \\
&= U''(\hat{\pi})E[(\bar{p}_1 y_1^* + \bar{p}_1\theta_1\eta_1 + y_1^*\sigma_1\varepsilon_1 + \sigma_1\theta_1\varepsilon_1\eta_1 + \bar{p}_2 y_2^* + \bar{p}_2\theta_2\eta_2 + y_2^*\sigma_2\varepsilon_2 + \sigma_2\theta_2\varepsilon_2\eta_2 \\
&\qquad - c_1(y_1^*, w) - c_2(y_2^*, w))\eta_1] \\
&= U''(\hat{\pi})(\bar{p}_1\theta_1 + y_1^*\sigma_1 E[\varepsilon_1\eta_1] + \sigma_1\theta_1 E[\varepsilon_1\eta_1^2] + \bar{p}_2\theta_2 E[\eta_1\eta_2] + y_2^*\sigma_2 E[\varepsilon_2\eta_1] + \sigma_2\theta_2 E[\varepsilon_2\eta_1\eta_2]).
\end{aligned}
$$

By inserting (6) into (4), we get:

$$
\begin{aligned}
(7)\qquad V_{\bar{p}_1} &= y_1^* E[U'(\pi^*)] + \theta_1 U''(\hat{\pi})(\bar{p}_1\theta_1 + y_1^*\sigma_1 E[\varepsilon_1\eta_1] + \sigma_1\theta_1 E[\varepsilon_1\eta_1^2] + \bar{p}_2\theta_2 E[\eta_1\eta_2] \\
&\qquad + y_2^*\sigma_2 E[\varepsilon_2\eta_1] + \sigma_2\theta_2 E[\varepsilon_2\eta_1\eta_2]) \\
&= y_1^*\alpha + \theta_1\beta(\bar{p}_1\theta_1 + y_1^*\sigma_1 E[\varepsilon_1\eta_1] + \sigma_1\theta_1 E[\varepsilon_1\eta_1^2] + \bar{p}_2\theta_2 E[\eta_1\eta_2] \\
&\qquad + y_2^*\sigma_2 E[\varepsilon_2\eta_1] + \sigma_2\theta_2 E[\varepsilon_2\eta_1\eta_2]),
\end{aligned}
$$

where we denote $\alpha = E[U'(\pi^*)]$ and $\beta = U''(\hat{\pi})$.

The first derivative of expected utility for the second crop is obtained similarly:

$$
\begin{aligned}
(8)\qquad V_{\bar{p}_2} &= y_2^*\alpha + \theta_2\beta(\bar{p}_1\theta_1 E[\varepsilon_1\eta_1] + y_1^*\sigma_1 E[\varepsilon_1\eta_2] + \sigma_1\theta_1 E[\varepsilon_1\eta_1\eta_2] + \bar{p}_2\theta_2 \\
&\qquad + y_2^*\sigma_2 E[\varepsilon_2\eta_2] + \sigma_2\theta_2 E[\varepsilon_2\eta_2^2]).
\end{aligned}
$$

Solving (7) and (8) simultaneously, we obtain the optimal supply functions for the two rotational crops:

$$
\begin{aligned}
(9)\qquad y_1^* = &\Big\{\Big(V_{\bar{p}_1} - \beta\theta_1\left(\bar{p}_1\theta_1 + \theta_1\sigma_1 E[\varepsilon_1\eta_1^2] + \bar{p}_2\theta_2 E[\eta_1\eta_2] + \theta_2\sigma_2 E[\varepsilon_2\eta_1\eta_2]\right)\Big) \times \left(\alpha + \beta\theta_2\sigma_2 E[\varepsilon_2\eta_2]\right) \\
&- \Big(V_{\bar{p}_2} - \beta\theta_2\left(\bar{p}_1\theta_1 E[\eta_1\eta_2] + \theta_1\sigma_1 E[\varepsilon_1\eta_1\eta_2] + \bar{p}_2\theta_2 + \theta_2\sigma_2 E[\varepsilon_2\eta_2^2]\right)\Big) \times \beta\theta_1\sigma_2 E[\varepsilon_2\eta_1]\Big\} \Big/ \\
&\Big\{\left(\alpha + \beta\theta_1\sigma_1 E[\varepsilon_1\eta_1]\right) \times \left(\alpha + \beta\theta_2\sigma_2 E[\varepsilon_2\eta_2]\right) - \beta^2\theta_1\theta_2\sigma_1\sigma_2 E[\varepsilon_2\eta_1]E[\varepsilon_1\eta_2]\Big\},
\end{aligned}
$$

$$
\begin{aligned}
(10)\qquad y_2^* = &\Big\{\Big(V_{\bar{p}_2} - \beta\theta_2\left(\bar{p}_1\theta_1 E[\eta_1\eta_2] + \theta_1\sigma_1 E[\varepsilon_1\eta_1\eta_2] + \bar{p}_2\theta_2 + \theta_2\sigma_2 E[\varepsilon_2\eta_2^2]\right)\Big) \times \left(\alpha + \beta\theta_1\sigma_1 E[\varepsilon_1\eta_1]\right) \\
&- \Big(V_{\bar{p}_1} - \beta\theta_1\left(\bar{p}_1\theta_1 + \theta_1\sigma_1 E[\varepsilon_1\eta_1^2] + \bar{p}_2\theta_2 E[\eta_1\eta_2] + \theta_2\sigma_2 E[\varepsilon_2\eta_1\eta_2]\right)\Big) \times \beta\theta_2\sigma_1 E[\varepsilon_1\eta_2]\Big\} \Big/ \\
&\Big\{\left(\alpha + \beta\theta_1\sigma_1 E[\varepsilon_1\eta_1]\right) \times \left(\alpha + \beta\theta_2\sigma_2 E[\varepsilon_2\eta_2]\right) - \beta^2\theta_1\theta_2\sigma_1\sigma_2 E[\varepsilon_2\eta_1]E[\varepsilon_1\eta_2]\Big\}.
\end{aligned}
$$

These supply functions are highly nonlinear in expected output prices, aggregate input price, and output price and quantity risk factors. Yet, we still need a clearer expression of $V_{\bar{p}_1}$ and $V_{\bar{p}_2}$. Since we do not know the true form of the indirect utility function, we use a second-order Taylor's series expansion of $V_{\bar{p}_1}$ and $V_{\bar{p}_2}$ around an arbitrary point A. Here we choose the point A as the mean of all variables which indicates $A = (\bar{\bar{p}}_1, \bar{\bar{p}}_2, \bar{\sigma}_1, \bar{\sigma}_2, \bar{\theta}_1, \bar{\theta}_2, \bar{w})$. Thus, we rewrite $V_{\bar{p}_1}$ and $V_{\bar{p}_2}$ as:

$$
\begin{aligned}
&V_{\bar{p}_1}(\bar{p}_1, \bar{p}_2, \sigma_1, \sigma_2, \theta_1, \theta_2, w) \\
&= V_{\bar{p}_1}(A) + V_{\bar{p}_1\bar{p}_1}(A)(\bar{p}_1 - \bar{\bar{p}}_1) + V_{\bar{p}_1\bar{p}_2}(A)(\bar{p}_2 - \bar{\bar{p}}_2) + V_{\bar{p}_1\sigma_1}(A)(\sigma_1 - \bar{\sigma}_1) \\
&\quad + V_{\bar{p}_1\sigma_2}(A)(\sigma_2 - \bar{\sigma}_2) + V_{\bar{p}_1\theta_1}(A)(\theta_1 - \bar{\theta}_1) + V_{\bar{p}_1\theta_2}(A)(\theta_2 - \bar{\theta}_2) + V_{\bar{p}_1 w}(A)(w - \bar{w}),
\end{aligned} \tag{11}
$$

$$
\begin{aligned}
&V_{\bar{p}_2}(\bar{p}_1, \bar{p}_2, \sigma_1, \sigma_2, \theta_1, \theta_2, w) \\
&= V_{\bar{p}_2}(A) + V_{\bar{p}_2\bar{p}_1}(A)(\bar{p}_1 - \bar{\bar{p}}_1) + V_{\bar{p}_2\bar{p}_2}(A)(\bar{p}_2 - \bar{\bar{p}}_2) + V_{\bar{p}_2\sigma_1}(A)(\sigma_1 - \bar{\sigma}_1) \\
&\quad + V_{\bar{p}_2\sigma_2}(A)(\sigma_2 - \bar{\sigma}_2) + V_{\bar{p}_2\theta_1}(A)(\theta_1 - \bar{\theta}_1) + V_{\bar{p}_2\theta_2}(A)(\theta_2 - \bar{\theta}_2) + V_{\bar{p}_2 w}(A)(w - \bar{w}).
\end{aligned} \tag{12}
$$

Inserting (11) and (12) into the two supply functions, we obtain the final forms of the supply functions for the two crops:

$$
\begin{aligned}
y_1^* = &\Big\{ \Big(V_{\bar{p}_1}(A) + V_{\bar{p}_1\bar{p}_1}(A)(\bar{p}_1 - \bar{\bar{p}}_1) + V_{\bar{p}_1\bar{p}_2}(A)(\bar{p}_2 - \bar{\bar{p}}_2) + V_{\bar{p}_1\sigma_1}(A)(\sigma_1 - \bar{\sigma}_1) \\
&+ V_{\bar{p}_1\sigma_2}(A)(\sigma_2 - \bar{\sigma}_2) + V_{\bar{p}_1\theta_1}(A)(\theta_1 - \bar{\theta}_1) + V_{\bar{p}_1\theta_2}(A)(\theta_2 - \bar{\theta}_2) + V_{\bar{p}_1 w}(A)(w - \bar{w}) \\
&- \beta\theta_1 \left(\bar{p}_1\theta_1 + \theta_1\sigma_1 E[\varepsilon_1\eta_1^2] + \bar{p}_2\theta_2 E[\eta_1\eta_2] + \theta_2\sigma_2 E[\varepsilon_2\eta_1\eta_2] \right) \Big) \times \left(\alpha + \beta\theta_2\sigma_2 E[\varepsilon_2\eta_2] \right) \\
&- \Big(V_{\bar{p}_2}(A) + V_{\bar{p}_2\bar{p}_1}(A)(\bar{p}_1 - \bar{\bar{p}}_1) + V_{\bar{p}_2\bar{p}_2}(A)(\bar{p}_2 - \bar{\bar{p}}_2) + V_{\bar{p}_2\sigma_1}(A)(\sigma_1 - \bar{\sigma}_1) \\
&+ V_{\bar{p}_2\sigma_2}(A)(\sigma_2 - \bar{\sigma}_2) + V_{\bar{p}_2\theta_1}(A)(\theta_1 - \bar{\theta}_1) + V_{\bar{p}_2\theta_2}(A)(\theta_2 - \bar{\theta}_2) + V_{\bar{p}_2 w}(A)(w - \bar{w}) \\
&- \beta\theta_2 \left(\bar{p}_1\theta_1 E[\eta_1\eta_2] + \theta_1\sigma_1 E[\varepsilon_1\eta_1\eta_2] + \bar{p}_2\theta_2 + \theta_2\sigma_2 E[\varepsilon_2\eta_2^2] \right) \Big) \times \beta\theta_1\sigma_2 E[\varepsilon_2\eta_1] \Big\} \Big/ \\
&\Big\{ \left(\alpha + \beta\theta_1\sigma_1 E[\varepsilon_1\eta_1] \right) \times \left(\alpha + \beta\theta_2\sigma_2 E[\varepsilon_2\eta_2] \right) - \beta^2\theta_1\theta_2\sigma_1\sigma_2 E[\varepsilon_2\eta_1] E[\varepsilon_1\eta_2] \Big\},
\end{aligned} \tag{13}
$$

$$
\begin{aligned}
y_2^* = \Big\{ & \Big(V_{\bar{p}_2}(A) + V_{\bar{p}_2\bar{p}_1}(A)(\bar{p}_1 - \bar{\bar{p}}_1) + V_{\bar{p}_2\bar{p}_2}(A)(\bar{p}_2 - \bar{\bar{p}}_2) + V_{\bar{p}_2\sigma_1}(A)(\sigma_1 - \bar{\sigma}_1) \\
& + V_{\bar{p}_2\sigma_2}(A)(\sigma_2 - \bar{\sigma}_2) + V_{\bar{p}_2\theta_1}(A)(\theta_1 - \bar{\theta}_1) + V_{\bar{p}_2\theta_2}(A)(\theta_2 - \bar{\theta}_2) + V_{\bar{p}_2 w}(A)(w - \bar{w}) \\
& - \beta\theta_2 \left(\bar{p}_1\theta_1 E[\eta_1\eta_2] + \theta_1\sigma_1 E[\varepsilon_1\eta_1\eta_2] + \bar{p}_2\theta_2 + \theta_2\sigma_2 E[\varepsilon_2\eta_2^2] \right) \Big) \times \left(\alpha + \beta\theta_1\sigma_1 E[\varepsilon_1\eta_1] \right) \\
& - \Big(V_{\bar{p}_1}(A) + V_{\bar{p}_1\bar{p}_1}(A)(\bar{p}_1 - \bar{\bar{p}}_1) + V_{\bar{p}_1\bar{p}_2}(A)(\bar{p}_2 - \bar{\bar{p}}_2) + V_{\bar{p}_1\sigma_1}(A)(\sigma_1 - \bar{\sigma}_1) \\
& + V_{\bar{p}_1\sigma_2}(A)(\sigma_2 - \bar{\sigma}_2) + V_{\bar{p}_1\theta_1}(A)(\theta_1 - \bar{\theta}_1) + V_{\bar{p}_1\theta_2}(A)(\theta_2 - \bar{\theta}_2) + V_{\bar{p}_1 w}(A)(w - \bar{w}) \\
& - \beta\theta_1 \left(\bar{p}_1\theta_1 + \theta_1\sigma_1 E[\varepsilon_1\eta_1^2] + \bar{p}_2\theta_2 E[\eta_1\eta_2] + \theta_2\sigma_2 E[\varepsilon_2\eta_1\eta_2] \right) \Big) \times \beta\theta_2\sigma_1 E[\varepsilon_1\eta_2] \Big\} \Big/ \\
& \Big\{ \left(\alpha + \beta\theta_1\sigma_1 E[\varepsilon_1\eta_1] \right) \times \left(\alpha + \beta\theta_2\sigma_2 E[\varepsilon_2\eta_2] \right) - \beta^2\theta_1\theta_2\sigma_1\sigma_2 E[\varepsilon_2\eta_1] E[\varepsilon_1\eta_2] \Big\}.
\end{aligned} \tag{14}
$$

We need to estimate the parameters of these supply functions which are α , β , $V_{\bar{p}_1}(A), V_{\bar{p}_2}(A)$ and each of the second-order partial derivatives of the indirect expected utility function with respect to output prices, input price, and output price and quantity risk factors. In addition, we include the state-level public research stock variable, *R,* in each supply function to represent technical change.

Sugar beet production in Washington changed abruptly on three occasions during our data period – in 1978 when the U&I Sugar Company closed its sugar processing plant, in 1994 when the Moses Lake plant began to operate, and in 2000 when it closed. To account for the influence of these external changes, we introduce two dummy variables in the sugar beet supply function. Dummy variable d_1 takes a value of 1 for the 1979-2006 period, 0 otherwise. Dummy variable d_2 takes a value of 1 for the period 1994-2000, 0 otherwise.

Empirically, the data series of $\bar{p}_1, \bar{p}_2, y_1, y_2, \sigma_1, \sigma_2, \theta_1, \theta_2$ and $E[\varepsilon_i\eta_j]$ in equations (13) and (14) are needed to estimate the supply functions. Since they are not observable directly, we need to generate the $\bar{p}_1, \bar{p}_2, y_1, y_2, \sigma_1, \sigma_2, \theta_1, \theta_2$ series and then calculate all the expectations of the risk factor products.

We follow the method developed by Chavas and Holt (1996) to generate the expected prices series, $\overline{p}_1$ and $\overline{p}_2$, for the Model 1 equations, where the price at time t is regressed on its lagged price.

(15) $\quad p_{it} = \gamma_i + \lambda_i p_{it-1} + u_{it} \quad i = 1,2,$

where p_{it} is the market price plus government programs payment for crop i at time t, p_{it-1} is crop i's previous year's price, γ_i and λ_i are drift and slope parameters for crop i, u_{it} is error term with $E[u_{it}] = 0$. Hence, the expected prices are:

(16) $\quad E[p_{it}] = \overline{p}_{it} = \gamma_i + \lambda_i p_{it-1} \quad i = 1,2.$

We use a similar method (Lapan and Moschini 1994) to generate the expected output series, y_1 and y_2, where output at time t is also dependent on their lagged values:

(17) $\quad q_{it} = \phi_i + \varphi_i q_{it-1} + v_{it} \quad i = 1,2,$

where q_{it} is the output level for crop i at time t, q_{it-1} is crop i's previous year's output level, ϕ_i and φ_i are drift and slope parameters for crop i, v_{it} is error term with $E[v_{it}] = 0$. Thus, the expected outputs are:

(18) $\quad E[q_{it}] = y_{it} = \phi_i + \varphi_i q_{it-1} \quad i = 1,2.$

We follow Chavas and Holt's (1996) method to generate risk factors $\sigma_1, \sigma_2, \theta_1, \theta_2$.

(19) $$\sigma_{it}^2 = \sum_{j=1}^{3} \omega_j (p_{it-j} - E_{it-j} p_{it-j})^2 \quad i = 1,2,$$

(20) $$\theta_{it}^2 = \sum_{j=1}^{3} \omega_j (q_{it-j} - E_{it-j} q_{it-j})^2 \quad i = 1,2,$$

where ω_j are 0.5, 0.33, 0.17 when $j = 1,2,3$. The variances of price and output are measured as a declining weighted sum of the squared difference of previous real values from expected values.

Then from the price equations, $p_i = \overline{p}_i + \sigma_i \varepsilon_i$, $i = 1, 2$, and output equations, $q_i = \overline{q}_i + \theta_i \eta_i = y_i + \theta_i \eta_i$, $i = 1, 2$, together with (19) and (20), we can calculate all the expectations of the products of risk factors in (13) and (14).

With these generated values of the independent and dependent variables and the formulas for the nonlinear supply response functions, we use nonlinear seemingly unrelated least squares to estimate the supply functions of the two rotational crops. We use this estimated model to not only calculate estimated supply elasticities but also to test several hypotheses about producer motivations. For example, if the producer is risk neutral, then $U''(\hat{\pi}) = \beta = 0$ and expected utility does not depend on output price or quantity risk, which means $V_{\sigma_i} = 0$ and $V_{\theta_i} = 0$. This implies that all the partial derivatives of V_{σ_i} and V_{θ_i} are also zero. Thus, we test risk neutrality by:

(21) $$\beta = V_{\overline{p}_1\sigma_1} = V_{\overline{p}_1\sigma_2} = V_{\overline{p}_2\sigma_1} = V_{\overline{p}_2\sigma_2} = V_{\overline{p}_1\theta_1} = V_{\overline{p}_1\theta_2} = V_{\overline{p}_2\theta_1} = V_{\overline{p}_2\theta_2} = 0.$$

We test for the absence of output price risk by:

(22) $$V_{\overline{p}_1\sigma_1} = V_{\overline{p}_1\sigma_2} = V_{\overline{p}_2\sigma_1} = V_{\overline{p}_2\sigma_2} = 0,$$

and the absence of output quantity risk by:

(23) $$V_{\overline{p}_1\theta_1} = V_{\overline{p}_1\theta_2} = V_{\overline{p}_2\theta_1} = V_{\overline{p}_2\theta_2} = 0.$$

Model 2 – Expected Utility Maximization under Output Price Risk

In this model, we ignore output quantity uncertainty while assuming farmers are risk averse and seek to maximize their expected utility considering output price risk only. We also impose some structure following Coyle (1992) by specifying a mean-variance utility function with stochastic output prices that is linear in expected profits, $E[\pi]$, and profit variance, $V[\pi]$:

(24) $$U = E[\pi] - \frac{\alpha}{2} V[\pi]$$

where α is a measure of risk aversion.

As in Model 1, the producer plants two rotational crops using an aggregate input. The farmer's profit function is:

(25) $$\pi = p_1 q_1 + p_2 q_2 - wx$$

where p_1, p_2 are crop prices (market prices adjusted for government programs payments), q_1, q_2 are crop output levels, w is aggregate input price, and x is aggregate input level. Hence,

(26) $$E[\pi(q_1, q_2, x)] = \overline{p}_1 q_1 + \overline{p}_2 q_2 - wx$$

(27) $$V[\pi(q_1, q_2, x)] = q_1^2 var(p_1) + q_2^2 var(p_2) + 2q_1 q_2 cov(p_1, p_2)$$

where $\overline{p}_1, \overline{p}_2$ are expected crop prices (including government program payments) at planting time, $var(p_1)$, $var(p_2)$, $cov(p_1,p_2)$ are variances and covariance of the crop prices.

The farmer is risk averse and maximizes her expected utility:

(28) $$\begin{aligned} &U^*(\overline{p}_1, \overline{p}_2, w, \mathrm{var}(p_1), \mathrm{var}(p_2), \mathrm{cov}(p_1, p_2)) \\ &= \max_{q_1, q_2, x} \left\{ U(q_1, q_2, x) = \overline{p}_1 q_1 + \overline{p}_2 q_2 - wx - \frac{\alpha}{2}\left[q_1^2 var(p_1) + q_2^2 var(p_2) + 2q_1 q_2 cov(p_1, p_2) \right] \right\} \end{aligned}$$

The following propositions apply to this dual specification of the price taking, risk averse, expected-utility maximizing producer:

(a) U^* is increasing in $\overline{p}$, decreasing in w, decreasing in Vp, where Vp is the covariance matrix of crop prices.

(b) U^* is linear homogeneous in $(\overline{p}, w, Vp)$.

(c) U^* is convex in prices $\overline{p}$ and w.

(d) $U^*(\cdot)$ is differentiable as follows:

(29) $$\frac{\partial U^*(\overline{p}, w, Vp)}{\partial \overline{p}_j} = q_j^*, j = 1, 2.$$

(30) $$\frac{\partial U^*(\bar{p}, w, Vp)}{\partial w} = -x$$

(31) $$\frac{\partial U^*(\bar{p}, w, Vp)}{\partial Vp_{jj}} = -\frac{\alpha}{2} q_j^{*2}, j = 1, 2.$$

(32) $$\frac{\partial U^*(\bar{p}, w, Vp)}{\partial Vp_{ij}} = -\alpha q_i^* q_j^*, i \neq j; i, j = 1, 2.$$

By specifying functional forms for the derivatives of this dual model with respect to prices $\bar{p}$ and w, we can get specific functional forms for the derivatives of the dual with respect to the elements of Vp, and can trace backwards to the dual utility function by Euler's theorem.

First we define general forms for the partial derivatives.

(33) $$\begin{aligned} q_j &= q_j\left(\frac{\bar{p}_1}{w}, \frac{\bar{p}_2}{w}, \frac{\operatorname{var}(p_1)}{w}, \frac{\operatorname{var}(p_2)}{w}, \frac{\operatorname{cov}(p_1, p_2)}{w}\right), j = 1, 2. \\ x &= x\left(\frac{\bar{p}_1}{w}, \frac{\bar{p}_2}{w}, \frac{\operatorname{var}(p_1)}{w}, \frac{\operatorname{var}(p_2)}{w}, \frac{\operatorname{cov}(p_1, p_2)}{w}\right) \end{aligned}$$

Since we do not have input quantity data for our specific crops, we are unable to estimate the input demand equation. Using seemingly unrelated regression method (SUR), we estimate the following system of supply functions, which are generalizations of those derived from a normalized quadratic profit function:

(34) $$\begin{aligned} q_{1t} &= a_1 + a_{11}\frac{p_{1t-1}}{w_t} + a_{12}\frac{p_{2t-1}}{w_t} + a_{13}R + b_{11}\frac{\operatorname{var}(p_{1t})}{w_t} + b_{12}\frac{\operatorname{var}(p_{2t})}{w_t} + b_{13}\frac{\operatorname{cov}(p_{1t}, p_{2t})}{w_t} + u_{1t} \\ q_{2t} &= a_2 + a_{21}\frac{p_{1t-1}}{w_t} + a_{22}\frac{p_{2t-1}}{w_t} + a_{23}R + b_{21}\frac{\operatorname{var}(p_{1t})}{w_t} + b_{22}\frac{\operatorname{var}(p_{2t})}{w_t} + b_{23}\frac{\operatorname{cov}(p_{1t}, p_{2t})}{w_t} + u_{2t} \end{aligned}$$

where R is the state level research stock variable. Assuming a Markov process, farmers take each crop's lagged price (adjusted for government payments) as the expected price for Model 2-4 equations. Consistent with proposition (b) of the utility function, this specification maintains the property that each supply function is homogeneous of degree zero in prices, variance, and covariance by dividing each of these variables by the input price index. Consistent with proposition (c), we maintain the property that the system of supply functions is convex in prices by reparameterizing the parameter matrix on the price variables using the Cholesky decomposition method. Consistent with proposition (d), we impose symmetry restrictions on the cross-price equations.

We derive variances and covariance of the crop prices following Chavas and Holt (1996) and introduce the same dummy variables in the sugar beets supply equation as in Model 1. We estimate and analyze the estimation results both under expected utility maximization (i.e., when we include the price variance and covariance items in equation (33)) and under risk-neutral profit maximization (i.e., when b_{ij}=0, i=1,2; j=1,2,3). We test for risk neutrality by testing the hypothesis that the coefficients on the variance and covariance terms are jointly zero.

Model 3 – Profit Maximization

We use panel data and estimate supply equations for canola and wheat based on profit maximization in a multi-state panel model. Because of the extremely limited time series for canola price and production data in each state, we do not introduce price risk into the supply functions but maintain the assumption of linear supply functions. Under price-taking, profit-maximizing behavior, the supply equations are nondecreasing in output prices, nonincreasing in aggregate input price, homogeneous of degree zero in prices, and convex in prices. If the profit function is twice continuously differentiable, the cross-price parameters are symmetric between the linear supply functions. Thus, we estimate the following supply functions as a fixed-effects panel data model allowing for differences between states in all parameters:

$$
(37)\qquad \begin{aligned}
q_{1mt} &= a_{1m} + a_{11m}\frac{p_{1mt-1}}{w_{mt}} + a_{12m}\frac{p_{2mt-1}}{w_{mt}} + a_{13m}R_{mt} + v_{1t} \\
q_{2mt} &= a_{2m} + a_{21m}\frac{p_{1mt-1}}{w_{mt}} + a_{22m}\frac{p_{2mt-1}}{w_{mt}} + a_{23m}R_{mt} + v_{2t}
\end{aligned}
$$

where *m=WA*, *ID*, *MN*, *ND* denotes Washington, Idaho, Minnesota, and North Dakota, respectively.

We also estimate this system of supply equations as a system of seemingly unrelated regressions. While we obtain results for all four states, we focus on the implications for Washington.

Model 4 – Pragmatic Alternatives

In addition to models that fully satisfy the expected utility or the profit maximization hypotheses, we also search for specifications of Washington corn and sugar beet supplies that meet the most important expectation under profit maximization, i.e., a positively-sloped own-price parameter, that is statistically significant. We focus attention on models that permit the short-run and long-run price elasticities to be distinguished; assuming Koyck distributed lags, the lagged dependent variable is included in the specification as a regressor. We consider simple linear and loglinear specifications based on profit maximization or expected utility maximization. Following a Markov process, lagged output prices (market plus government payments) are the expected output prices. So the basic specification is as follows:

$$
(38)\qquad q_{it} = a_i + a_{ii}p_{it-1} + \sum_j a_{ij}p^*_{jt} + a_{iy}q_{it-1}
$$

where $p*$ is a subset of the vector of other expected output prices, the input price index, and research stock or year. In some cases the expected output prices are divided by the input price index, thus maintaining homogeneity of degree zero as also implied by expected profit maximization.

We estimate Models 1-4 using state-level data. Depending on the model, we maintain the hypothesis that each state acts as though it were an optimizing (either expected utility, profit, or quasi-profit maximizing) producer. While the assumption that a state acts as though it were an optimizing producer is an important abstraction from reality, Lim and Shumway's (1992) nonparametric test results failed to reject the most binding version of this hypothesis for the State of Washington.

Results

In this section, we report and discuss implications of the estimated Washington parameters for corn and potato supplies and for sugar beet and alfalfa hay supplies based on Models 1, 2 and 4. We report similar findings for canola and wheat for each of four states based on Model 3.

Results from Model 1

Estimated parameters for the Washington corn and potato supply equations, estimated elasticities, and hypothesis tests from Model 1 are reported in Table 1. Twelve of the 19 parameter estimates are statistically significant at the 10% level (ten at the 5% level). The corn own-price elasticity is also significant, but it is negative which implies a downward sloping output supply contrary to strong theoretical expectations. The potato own-price elasticity is also negative although statistically insignificant. Hypotheses of risk neutrality and absence of either output price or output quantity risk are all rejected.

Estimated parameters, elasticities, and hypothesis tests for the Washington sugar beet and alfalfa hay supply equations from Model 1 are reported in Table 2. Although two more parameters are estimated in this system of equations, only seven are statistically significant at the 10% level (five at the 5% level). Sugar beet own-price elasticity is negative but insignificantly different from zero. The alfalfa hay own-price elasticity is positive but also insignificant. Of the three hypotheses tested, only the absence of output quantity risk is not rejected.

Given the small number of statistically significant parameters in the sugar beet – alfalfa hay equations and the failure of Model 1 to provide positively-sloped estimates of the own-price elasticity of either biofuel feedstock, we must conclude that this model does not provide a statistically adequate or economically meaningful fit of the data. Consequently, we turn to other models of supply for these commodities.

Results from Model 2

Model 2 parameter estimates for corn and potato supply functions are reported in Table 3. Two sets of estimates are provided. The first presumes that producers are risk-neutral in maximizing expected utility (i.e., they maximize expected profit) while the second presumes they also account for price risk in maximizing expected utility.

Under risk neutrality, four of the seven parameter estimates are statistically significant at the 10% level (three at the 5% level). Except for the intercept, all parameters in the corn supply equation are statistically significant. The own-price and cross-price elasticities are also significant. The corn own-price elasticity is small while the potato own-price elasticity is very large but statistically insignificant. The cross-price elasticities are negative, implying the two crops are substitutes. We also observe that corn supply is more dependent on potato price than corn price. Although the magnitude of the own-price elasticity estimate is small for corn and large for potatoes, when considered along with the cross-price elasticities, they do reflect one important point. Corn is a very low-value crop relative to potatoes and is often grown as a rotation crop with potatoes. Thus, it is expected potato price that drives the production of potatoes. And, since they are grown in rotation, it also drives the production of corn.

We next examine whether price risk is statistically significant and whether it moderates the supply elasticity estimates. When supply response is couched within the framework of maximizing expected utility under output price risk, five of 13 parameters estimates are statistically significant at the 10% level (and at the 5% level). However, only one intercept parameter and the parameters on the research stock and corn variance are significant. Consequently, although positive, neither own-price elasticity is statistically significant. The hypothesis of risk neutrality is rejected, which implies that the expected utility maximization framework is preferred to the assumption of risk-neutral, profit-maximizing behavior. Thus, our assessment of the historical data via each of the three estimated sets of Model 1 and Model 2 supply equations suggests that Washington corn is unlikely to become a major source of biofuel feedstock.

Table 4 provides the estimation results for the sugar beet and alfalfa hay supply equations both under risk neutrality and when considering price risk. Under risk neutrality, five of nine parameter estimates are significant at the 10% level (five also at the 5% level). Except for the alfalfa hay price and the second dummy variable, all parameter estimates in the sugar beet equation are significant. The sugar beet own-price elasticity is significant and approximately unitary while the alfalfa hay own-price elasticity is small and insignificant.

When output price risk is considered, seven of 15 parameter estimates are statistically significant. They include the parameters on sugar beet price and variance in the sugar beet equation. The sugar beet own-price elasticity is again significant and a little larger than when estimated under the assumption of price neutrality. The price covariance terms were insignificant in both supply functions, so they were dropped and the supply equations considering price variances were re-estimated. The drop of covariance terms doesn’t change the results much. The same parameters are statistically significant, and the sugar beet own-price elasticity is significant and unitary. The hypothesis of risk neutrality is rejected in favor of expected utility maximization with output price risk.

The relatively large and consistent magnitudes of the Model 2 own-price elasticity estimates for sugar beets suggest that this crop has potential to become a major biofuel feedstock in Washington. Its supply can be encouraged by an increase in the market price and/or the government subsidy.

Results from Model 3

The parameter estimates for Washington, Idaho, Minnesota, and North Dakota wheat and canola supply equations are reported in Table 5. Only seven of the 28 parameter estimates are significant at the 10% level (six at the 5% level). They include five parameters for North Dakota supplies, the canola own-price parameter for Minnesota, and the wheat own-price parameter for Washington.

Elasticity estimates at the data means are reported in Table 6. The only significant elasticity in Washington is the wheat own-price elasticity. The canola own-price elasticity is economically trivial as well as statistically insignificant. The cross-price elasticity is positive which implies wheat and canola are complements, but it is statistically insignificant. Qualitative results for Idaho are similar to Washington as is the estimated canola own-price elasticity magnitude. Only in Minnesota is the canola own-price elasticity significant. Although North Dakota produced more than 90% of the U.S. canola crop in 2004, its own-price elasticity is trivial and insignificant, but its cross-price elasticity and wheat own-price and cross-price elasticity are significant. In North Dakota, canola and wheat are substitutes, and canola production is much more sensitive to wheat price than to its own price.

Washington contributed 0.35% of the U.S. canola production and 6.65% of U.S. wheat production in 2004. The State's canola supply is trivial, and our analysis suggests that it currently is largely unresponsive to its expected price. Other recent empirical evidence supports this finding by noting that high production risks associated with producing this crop in Eastern Washington make it uncompetitive with other crops (Zaikin, Young, and Schillinger 2007). Thus, the evidence from both econometric analysis and production trials suggests that, despite its high oil yield for biodiesel, Washington-produced canola is unlikely to be a major source of biofuel feedstock in the near future.

Results from Model 4

Parameter estimates for other models of corn and sugar beet supply that satisfied the pragmatic condition are reported in Table 7. In each model reported, both the own-price coefficient and the coefficient on the lagged dependent variable were significant at the 10% level and typically at the 5% level. Alfalfa hay price, research stock, and year were never significant in the corn supply equations. Inclusion of research stock resulted in a higher $Rbar^2$ value in the corn supply equations, but adding alfalfa hay price consistently lowered it, as did replacing research stock with year. Functional form had the largest impact on $Rbar^2$ values. Alfalfa hay price, potato price, and year were never significant in the sugar beet supply equations. Functional form had the biggest impact on $Rbar^2$ values. All loglinear corn supply equations had higher $Rbar^2$ values than any of the linear equations, and all linear sugar beet supply equations had higher $Rbar^2$ values than any of the loglinear equations.

Both short-run and long-run own-price elasticity estimates are reported for each of the pragmatic models in Table 8. For the linear equations, they are computed at the data means. The estimated elasticities are quite sensitive to model specification, and in the case of sugar beets, to functional form.

The short-run corn supply elasticities vary from 0.46 to 1.22 when computed with the linear models and from 0.50 to 0.68 when computed with the loglinear models. The average of all linear models is 0.79 and the average of all loglinear models is 0.60. The elasticity from the models with highest Rbar^2 values is 0.78 for the linear and 0.50 for the loglinear. Since the loglinear models had consistently and substantially higher Rbar^2 values and since Models 1-2 did not render corn own-price supply elasticities that were both economically meaningful and statistically significant, we rely mainly on the Model 4 loglinear models for our "best" estimates of the corn short-run supply elasticity: 0.6 (the loglinear mean) with a possible range from 0.5 (loglinear minimum) to 0.8 (linear mean).

Their long-run elasticities vary between 1.35 and 4.64 from the linear models and between 2.39 and 3.79 from the loglinear models. Averages are 2.54 and 3.13, respectively. Elasticities from models with highest Rbar^2 values are 2.00 and 2.39, respectively. Since the estimates from models with highest Rbar^2 values are lower than either average, we consider them in our best estimates of the corn long-run supply elasticity: 2.4 (loglinear highest Rbar^2) with a possible range from 2.0 (linear highest Rbar^2) to 3.1 (loglinear mean).

The short-run sugar beet elasticities vary from 0.24 to 0.89 when computed with the linear models and from 1.13 to 3.38 when computed with the loglinear models. The average of all linear models is 0.62 and the average of all loglinear models is 2.33. The elasticity from the models with highest Rbar^2 values is 0.71 for the linear and 3.38 for the loglinear. Since the linear models had consistently and substantially higher Rbar^2 values, we rely mainly on them and Model 2 estimates for our best estimates of the sugar beet short-run supply elasticity: 0.7 (linear highest Rbar^2) with a possible range from 0.6 (linear mean) to 1.1 (Model 2 mean and loglinear minimum).

Their long-run elasticities vary from 0.31 to 1.10 from the linear models and from 2.58 to 7.47 from the loglinear models. Averages are 0.79 and 5.22, respectively. Elasticities from models with highest $Rbar^2$ values are 0.89 and 7.47, respectively. We rely on the linear models for our best estimate of the sugar beet long-run supply elasticity, 0.9 (linear highest $Rbar^2$), but consider the lower end of the loglinear range for our upper estimate to provide a possible range from 0.7 (linear 3rd lowest) to 2.6 (loglinear minimum).

Decision Making and Policy Implications

From these empirical results, we conclude that corn and sugar beets could become important sources of locally-produced biofuel feedstock in Washington. Sugar beets demonstrate the largest short-run supply elasticities, so supplies of this crop are expected to show the quickest response to price or subsidy stimuli. Although current production of Washington sugar beets is very small, that is due to the lack of a sugar beet processing plant in the State. Washington sugar beet producers must incur very high transportation costs to get their crop to market. Should appropriately located ethanol plants be built to handle sugar beets, we might reasonably expect Washington sugar beet production to quickly return to the levels of the early 1970s.

Although the short-run elasticity estimates for corn are somewhat smaller than for sugar beets, long-run elasticity estimates are greater. Thus, corn is expected to be more responsive to price and subsidy stimuli during the 2012-2020 period than sugar beets, so it could become the more important source of in-state biofuel feedstock with similar economic incentives.

Canola is hard to judge due to the limited quantity produced in the state and the short time period for which reliable state-level data are available in the U.S. Further, recent production experience in the State has not been promising (Young 2008). Consequently, we draw no conclusions about the prospects for this source of in-state biofuel feedstock.

Under current legislation, Washington's Renewable Fuel Standard requires certain licensees in the fuel production chain to report evidence that at least two percent of gasoline and diesel sold in the State contain ethanol or biodiesel, respectively, by December 2008 (RCW 19.112.110, RCW 19.112.120). For example, for a 2.7 billion gallon fuel market, this implies a minimum requirement of 54 million gallons of biofuel. Currently there is virtually no use of Washington biomass for biofuel production (Yoder et. al., 2007).

For in-state feedstocks to satisfy the mandated biofuel production demand, a subsidy for locally produced corn and sugar beets used as biofuel feedstock is likely to generate the quickest and most visible response from Washington crop producers. Biofuel conversion rates of these two crops are 0.36 bushel of corn (Lyons 2008) or 80.6 lbs of sugar beets (Salassi, 2007) for a gallon of ethanol.

Just over 3/4 of the current production of Washington corn or 2/3 of the average production of Washington sugar beets in the 1970s (with yield increases similar to those in Idaho) would be sufficient to meet the mandated biofuel production from in-state feedstocks for a 2.7 billion gallon fuel market (based on Young 2008). Consequently, with ethanol processing facilities located in appropriate places and capable of utilizing these crops, production that would be reasonably expected at current prices would be more than sufficient to meet the mandate from in-state feedstock production. The only incentive needed would be that required to compete with existing buyers of in-state production of these and competitive crops. Since there is no current competitor for sugar beets, it is unlikely much of a premium would be required to secure the entire sugar beet crop for biofuel. For corn, a modest premium may be needed to compete with current uses of in-state production, but it should not be great. The Washington corn market reflects the Midwest corn market plus transportation costs, e.g.., average corn price in

Washington has averaged 20% higher than the Iowa price during the period 2003-2007.

Assuming that a 10% biofuel feedstock subsidy would be sufficient to secure the entire Washington corn and sugar beet production for biofuels, they would supply more than 5% of the total Washington fuel market. To achieve 10% of the current fuel market would require an estimated additional 120% subsidy in the short run and an estimated 50% subsidy in the long run.

Conclusions

In this paper, we estimated a wide array of supply equations for three potential biofuel feedstock crops (corn, sugar beets, and canola) in Washington. We considered a range of models both for the feedstock crops and for rotational crops. One set of models fully embodied the theoretical structure implied by expected utility maximization. Other models partially embodied this framework. Examining the comparative statics results of the models, we conclude that Washington corn and sugar beets are important potential sources of biofuel feedstock in the State. Corn is expected to have the greatest potential because it has the largest long-run elasticity, and the supply can be encouraged by an increase in the market price and/or government subsidy. Recovery in the sugar beet industry also has significant potential. The potential of canola is less clear, largely because of data limitations and anecdotal evidence that canola doesn't compete well in either current or historical markets with other crops produced in the State.

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Table 1. Estimated Washington Corn and Potato Supply Equations, Model 1

Variable/ Parameter	Coefficient	P-value	Supply Elasticity/ Hypothesis Test	Value	P-value
$\alpha = E[U'(\pi^*)]$	0.43534E-03	0.00000	Corn own-price elasticity	-1.2522	0.00000
$\beta = U''(\hat{\pi})$	-0.73148E-04	0.00094			
$V_{\bar{p}_1}(A)$	-0.68662E-05	0.80580	Corn cross-price elasticity	0.10005	0.61356
$V_{\bar{p}_1\bar{p}_1}(A)$	-0.64870E-04	0.00000			
$V_{\bar{p}_1\bar{p}_2}(A)$	0.53385E-05	0.62227	Potato own-price elasticity	-0.26488E-01	0.82670
$V_{\bar{p}_1\sigma_1}(A)$	0.30463E-04	0.28767			
$V_{\bar{p}_1\sigma_2}(A)$	0.43084E-04	0.00968	Potato cross-price elasticity	0.13519E-01	0.62272
$V_{\bar{p}_1\theta_1}(A)$	0.59060E-03	0.00000			
$V_{\bar{p}_1\theta_2}(A)$	0.48295E-04	0.25473	Test: Risk Neutrality	reject	0.00000
$V_{\bar{p}_1 w}(A)$	0.14778E-04	0.00004			
$V_{\bar{p}_2}(A)$	0.86937E-03	0.00000	Test: Absence of Output Price Risk	reject	0.01509
$V_{\bar{p}_2\bar{p}_2}(A)$	-0.12794E-04	0.80117			
$V_{\bar{p}_2\sigma_1}(A)$	-0.26175E-03	0.05054	Test: Absence of Output Quantity Risk	reject	0.00000
$V_{\bar{p}_2\sigma_2}(A)$	0.49174E-04	0.61284			
$V_{\bar{p}_2\theta_1}(A)$	-0.88508E-03	0.09245			
$V_{\bar{p}_2\theta_2}(A)$	0.51741E-03	0.01718			
$V_{\bar{p}_2 w}(A)$	0.14541E-03	0.00000			
R (research stock) in (13)	0.94984E-05	0.00000			
R (research stock) in (14)	0.95870E-06	0.92015			

Note: Elasticity estimates are computed at the data means.

Table 2. Estimated Washington Sugar beet and Alfalfa Hay Supply Equations, Model 1

Variable/ Parameter	Coefficient	P-value	Supply Elasticity/ Hypothesis Test	Value	P-value
$\alpha = E[U'(\pi^*)]$	0.45151E-03	0.00000	Sugar beets own-price elasticity	-0.80156	0.18913
$\beta = U''(\hat{\pi})$	-0.11674E-16	1.00000			
$V_{\bar{p}_1}(A)$	0.14327E-03	0.33228	Sugar beets cross-price elasticity	-0.17798	0.66553
$V_{\bar{p}_1\bar{p}_1}(A)$	-0.35425E-04	0.18760			
$V_{\bar{p}_1\bar{p}_2}(A)$	-0.74118E-05	0.66553	Alfalfa hay own-price elasticity	0.12125E-01	0.87713
$V_{\bar{p}_1\sigma_1}(A)$	0.16287E-03	0.00003			
$V_{\bar{p}_1\sigma_2}(A)$	-0.22729E-03	0.01008	Alfalfa hay cross-price elasticity	-0.26055E-01	0.66553
$V_{\bar{p}_1\theta_1}(A)$	0.64208E-04	0.59474			
$V_{\bar{p}_1\theta_2}(A)$	0.14685E-03	0.44677	Test: Risk Neutrality	reject	0.00004
$V_{\bar{p}_1 w}(A)$	-0.20230E-04	0.05514			
$V_{\bar{p}_2}(A)$	0.87234E-03	0.00000	Test: Absence of Output Price Risk	reject	0.00002
$V_{\bar{p}_2\bar{p}_2}(A)$	0.32500E-05	0.87711			
$V_{\bar{p}_2\sigma_1}(A)$	-0.37749E-05	0.91580	Test: Absence of Output Quantity Risk	not reject	0.51162
$V_{\bar{p}_2\sigma_2}(A)$	-0.99658E-04	0.13599			
$V_{\bar{p}_2\theta_1}(A)$	0.12593E-04	0.85986			
$V_{\bar{p}_2\theta_2}(A)$	0.19951E-03	0.08869			
$V_{\bar{p}_2 w}(A)$	0.44757E-04	0.00004			
R (research stock) in (13)	-0.13090E-05	0.90111			
R (research stock) in (14)	-0.56449E-05	0.47348			
d_1 (dummy in (14))	0.35673E-01	0.76151			
d_2 (dummy in (14))	0.29244E-03	0.99541			

Note: Elasticity estimates are computed at the data means.

Table 3. Estimated Washington Corn and Potato Supply Equations, Model 2

Parameter (Equation 32)	Risk-Neutral, Profit Maximization Equations		Expected Utility Maximization Equations	
	Coefficient	P-value	Coefficient	P-value
a_1	-0.14896	0.16209	-0.29705	0.00018
a_{11}	0.33004E-02	0.07429	0.29662E-18	1.00000
$a_{12} = a_{21}$	-0.22401	0.03473	-0.45386E-19	1.00000
a_{13}	0.17062E-04	0.00000	0.19160E-04	0.00000
a_2	-0.14982E-01	0.98395	-0.69234	0.37493
a_{22}	543.65	0.16982	0.40257	0.59556
a_{23}	0.83123E-04	0.00000	0.93643E-04	0.00000
b_{11}	—	—	-1.6811	0.01552
b_{12}	—	—	0.32392	0.37042
b_{13}	—	—	1.1196	0.12847
b_{21}	—	—	-14.578	0.00074
b_{22}	—	—	-1.2982	0.56171
b_{23}	—	—	7.0164	0.11724
Corn own price elasticity	0.77742E-02	0.07429	0.69870E-18	1.00000
Corn cross price elasticity	-0.42201	0.03473	-0.85502E-19	1.00000
Potatoes own price elasticity	136.41	0.16982	0.10101	0.59556
Potatoes cross price elasticity	-0.70281E-01	0.03473	-0.14239E-19	1.00000
Test: Risk Neutrality	—		Reject	

Notes: Parameters with a first subscript of 1 are for the corn equation and those with a first subscript of 2 are for the potatoes equation. Elasticity estimates are computed at the data means.

Table 4. Estimated Washington Sugar Beet and Alfalfa Hay Supply Equations, Model 2

Parameter (Equation 32)	Risk-Neutral, Profit Maximization Equations		Expected Utility Maximization Equations			
			Including Variance and Covariance		Including Variance Only	
	Coefficient	P-value	Coefficient	P-value	Coefficient	P-value
a_1	0.85988	0.00141	0.76015	0.00069	0.75291	0.00225
a_{11}	0.45892	0.00263	0.51117	0.00260	0.42876	0.01318
$a_{12} = a_{21}$	-0.69216E-01	0.64611	-0.19204	0.13270	-0.12772	0.44756
a_{13}	-0.28219E-04	0.00001	-0.21512E-04	0.00024	-0.20604E-04	0.00051
a_2	1.7110	0.00000	1.3643	0.00000	1.4506	0.00000
a_{22}	0.15428	0.57433	0.72150E-01	0.41776	0.32772	0.56019
a_{23}	-0.13539E-04	0.34273	0.10263E-04	0.47834	0.40922E-05	0.77288
c_1(dummy d1)	0.56646	0.01947	0.29925	0.16532	0.39628	0.11737
c_2(dummy d2)	0.83391E-01	0.39049	0.72070E-01	0.42158	0.65700E-01	0.49080
b_{11}	—	—	1.2151	0.00003	0.91976	0.00006
b_{12}	—	—	-2.3310	0.01112	-2.8806	0.00125
b_{13}	—	—	-1.2529	0.15490	—	—
b_{21}	—	—	-0.71506E-02	0.98790	0.27739	0.47141
b_{22}	—	—	-2.9152	0.00149	-2.7006	0.00785
b_{23}	—	—	0.69389	0.42603	—	—
Sugar beets own-price elasticity	1.0765	0.00263	1.1991	0.00260	1.0058	0.01318
Sugar beets cross-price elasticity	-0.15805	0.64611	-0.43852	0.13270	-0.29164	0.44756
Alfalfa hay own-price elasticity	0.57265E-01	0.57433	0.26781E-01	0.41776	0.12164	0.56019
Alfalfa hay cross-price elasticity	-0.26394E-01	0.64611	-0.73232E-01	0.13270	-0.48704E-01	0.44756
Test: Risk Neutrality	—		reject		reject	

Notes: Parameters with a first subscript of 1 are for the sugar beets equation and those with a first subscript of 2 are for the alfalfa hay equation. Elasticity estimates are computed at the data means.

Table 5. Estimated WA, ID, MN, ND Canola and Wheat Supply Equations, Model 3

Parameter (Equation 35) [a]	Coefficient	P-value	Parameter (Equation 35)[a]	Coefficient	P-value
a_{1WA}	0.39165E-01	0.94805	a_{13MN}	-0.14670E-05	0.82849
a_{1ID}	0.11538	0.63805	a_{13ND}	0.12348E-03	0.00000
a_{1MN}	0.21275E-01	0.94213	a_{2WA}	2.6953	0.21272
a_{1ND}	-2.1296	0.00000	a_{2ID}	1.6460	0.35714
a_{11WA}	0.36786E-16	1.00000	a_{2MN}	-1.3603	0.51665
a_{11ID}	0.12869E-15	1.00000	a_{2ND}	-4.5965	0.14849
a_{11MN}	0.14722	0.09933	a_{22WA}	1.2474	0.00337
a_{11ND}	0.20243E-14	1.00000	a_{22ID}	0.42298	0.55992
$a_{12WA}= a_{21WA}$	0.19671E-01	0.78165	a_{22MN}	0.75460	0.33099
$a_{12ID}= a_{21ID}$	-0.39710E-01	0.70158	a_{22ND}	3.2789	0.00000
$a_{12MN}= a_{21MN}$	-0.11191	0.30223	a_{23WA}	-0.47670E-04	0.50126
$a_{12ND}= a_{21ND}$	-0.41870	0.00000	a_{23ID}	-0.54989E-04	0.60676
a_{13WA}	-0.14582E-05	0.94042	a_{23MN}	0.60577E-04	0.22320
a_{13ID}	-0.62145E-05	0.67444	a_{23ND}	0.25859E-03	0.04243

Note: Parameters with a first subscript of 1 are from the canola equation, and those with a first subscript of 2 are from the wheat equation.

Table 6. Estimated WA, ID, MN, ND Canola and Wheat Supply Elasticities, Model 3

State	Elasticity	Value	P-value	State	Elasticity	Value	P-value
WA	Canola own-price	0.13135E-15	1.00000	MN	Canola own-price	0.49204	0.09933
	Canola cross-price	0.48603E-01	0.78165		Canola cross-price	-0.31827	0.30223
	Wheat own-price	0.11798	0.00337		Wheat own-price	0.82158E-01	0.33099
	Wheat cross-price	0.26890E-02	0.78165		Wheat cross-price	-0.14318E-01	0.30223
ID	Canola own-price	0.32997E-15	1.00000	ND	Canola own-price	0.63658E-14	1.00000
	Canola cross-price	-0.96145E-01	0.70158		Canola cross-price	-1.1634	0.00000
	Wheat own-price	0.39205E-01	0.55992		Wheat own-price	0.34879	0.00000
	Wheat cross-price	-0.38978E-02	0.70158		Wheat cross-price	-0.50405E-01	0.00000

Note: Elasticity estimates are computed at the data means.

Table 7. Estimated Pragmatic Corn and Sugar Beet Supply Equations, Model 4

		Expected Price						Dummy Variables			
Equation Estimated	Lagged Dependent Variable	Alfalfa Hay	Corn	Potatoes	Sugar Beets	Research Stock	Year	1979-2006	1994-2000	Constant	$Rbar^2$
Corn Supply											
Linear Models											
1	0.6689027***		1921.757*			0.0001576				-5490.843**	0.8449
	(0.0987444)		(1130.238)			(0.0001408)				(2172.004)	
2	.6840833***		2548.957***				49.47761			-100939.5	0.8432
	(.0995547)		(865.1037)				(56.07511)			(109711.6)	
3	.6634297***		1915.382*	935.4707			-20.45288			36308.23	0.8449
	(.1004675)		(1007.065)	(772.8343)			(772.8343)			(157357.2)	
4	.6893397***		4062.043***	1242.877	-216.7295*		15.35401			-35393.03	0.8552
	(.0979848)		(1459.871)	(763.0145)	(109.8519)		(79.70046)			(156366)	
5	.6319536***	-32.40101	3183.881**	1716.199**	-228.5028**	.0002248				-7681.179***	0.8627
	(.1082996)	(36.57625)	(1439.893)	(705.6378)	(110.8991)	(.000138)				(2346.021)	
6	.7161478***	-27.61287	3935.362***	1648.981**	-189.489*					-5395.885***	0.8570
	(.0971127)	(37.20351)	(1391.864)	(718.8361)	(110.4958)					(1918.641)	
7	.6950212***		3981.902***	1336.852**	-211.9105*					-5271.949***	0.8586
	(.0923375)		(1382.815)	(579.7838)	(105.7023)					(1900.863)	
8	.6110042***		3270.988**	1349.374**	-252.9368**	.0002149				-7436.79***	0.8634
	(.1054012)		(1432.661)	(569.8187)	(107.1247)	(.0001372)				(2323.466)	
9	.736188***	-60.34189	5148.611***	1822.728**	-170.9623	-5464.411^^				-6986.912	0.8405
	(.1013053)	(46.05201)	(1758.936)	(762.9188)	(115.3343)	(4254.465)				(2493.023)	
Loglinear Models											
1	.7915413***		.4986904**				.0041957			-6.870308	0.9169
	(.0812465)		(.1899111)				(.0053691)			(10.08196)	
2	.7981174***		.5502346**	-.0736638			.0056779			-9.831985	0.9151
	(.0843884)		(.2451104)	(.2178488)			(.0069757)			(13.43689)	
3	.8133663***		.6711882*	-.0478619	-.1357389		.0061684			-10.63973	0.9135
	(.0905856)		(.347879)	(.2259884)	(.2744626)		(.0071104)			(13.6604)	
4	.8203828***	-.2078988	.6802686**				.0089789			-15.95547	0.9160
	(.0906036)	(.2824352)	(.311952)				(.0084481)			(15.97191)	
Sugar Beet Supply											
Linear Models											
1	.2277533**	.4074568	-309.5019**	-25.69651	24.87037**	.0000223*		-1655.835***	580.7694***	1014.777***	0.9129
	(.0964325)	(3.270343)	(122.1356)	(63.62046)	(10.34088)	(.0000128)		(226.8962)	(120.7687)	(230.2795)	
2	.2328273**		-309.8023**		23.51467***	.0000223*		-1664.881***	563.457***	995.146***	0.9170
	(.0919974)		(118.0703)		(8.42635)	(.0000125)		(211.0618)	(104.9743)	(219.5038)	
3	.2359719**				10.23303*		8.064659	-1598.239***	496.4384***	-14819.26	0.9062

	(.0901363)				(5.812752)		(5.836494)	(205.7173)	(114.0873)	(11419.09)	
4	.2641236***				13.6813**			-1449.708***	537.9865***	957.3756***	0.9041
	(.0887718)				(5.307681)			(177.3332)	(111.2672)	(177.247)	
5	.1899675**	-2.497819^	-137.5676^***	-30.47717^	13.73695^***	.00000274		-1691.197***	572.3185***	1867.406***	0.9222
	(.0897308)	(3.013169)	(49.6073)	(31.50222)	(4.689871)	(.0000135)		(228.4763)	(107.9435)	(408.3241)	
6	.189804**	-2.733841^	-122.3187^**	-31.20118^	14.45165^***		5.322182	-1706.105***	554.1005***	-8674.608	0.9234
	(.0853348)	(2.752779)	(45.726)	(30.86345)	(4.301186)		(6.591416)	(196.3809)	(105.3887)	(13127.3)	
7	.215316**		-160.0996^***		11.67694^**	-.00000127		-1625.439***	529.969***	1743.677***	0.9220
	(.0872597)		(46.4224)		(4.472596)	(.0000121)		(223.8595)	(103.8546)	(387.0026)	
8	.2070937**		-142.4516^***		11.41112^***		3.604834	-1667.826***	521.2627***	-5476.852	0.9226
	(.081799)		(44.08467)		(3.770652)		(6.450292)	(193.0124)	(103.5075)	(12870.76)	
9	.2120759**		-156.9868^***		11.42667^***			-1638.455***	531.957***	1714.576***	0.9239
	(.0806097)		(35.28788)		(3.737997)			(184.1163)	(100.8451)	(266.843)	
Loglinear Models											
1	.5628604***				2.546244***	-2.916542**		-2.876583***	2.133675***	45.18997**	0.8419
	(.0940932)				(.9160455)	(1.406183)		(.7423649)	(.58055)	(21.83411)	
2	.5472171***		-1.671036		3.380183***	-2.689384*		-3.055329***	2.207481***	40.28977**	0.8435
	(.0945611)		(1.413959)		(1.15275)	(1.412402)		(.7540357)	(.5810584)	(22.11875)	
3	.5629378***				1.127458*			-3.181689***	2.106524***	.0728067	0.8292
	(.0978086)				(.6333273)			(.7563763)	(.6033205)	(1.956738)	
4	.5438571***		-2.037433		2.278983**			-3.370655***	2.199092***	-1.617336	0.8332
	(.0975984)		(1.44605)		(1.029391)			(.7593865)	(.599809)	(2.275507)	

Notes: Standard errors are in parentheses; * denotes significant at the 10% level, ** at the 5% level, and *** at the 1% level; ^ denotes expected output price variable is divided by the input price index, and ^^ denotes own-price variance.

Table 8. Own-Price Elasticity Estimates, Pragmatic Models, Model 4

Regressors	Lagged Dependent Variable Coefficient	Own-Price Coefficient	Rbar^2	Own-Price Elasticity Estimate Short Run	Long Run
Corn Supply:					
Linear Models					
1	0.6689027	1921.757	0.8449	0.457	1.380
2	.6840833	2548.957	0.8432	0.606	1.919
3	.6634297	1915.382	0.8449	0.456	1.353
4	.6893397	4062.043	0.8552	0.966	3.110
5	.6319536	3183.881	0.8627	0.757	2.057
6	.7161478	3935.362	0.8570	0.936	3.297
7	.6950212	3981.902	0.8586	0.947	3.105
8	.6110042	3270.988	0.8634	0.778	2.000
9	.736188	5148.611	0.8405	1.224	4.641
Linear Model Average				0.792	2.540
Loglinear Models					
1	.7915413	.4986904	0.9169	0.499	2.392
2	.7981174	.5502346	0.9151	0.550	2.726
3	.8133663	.6711882	0.9135	0.671	3.596
4	.8203828	.6802686	0.9160	0.680	3.787
Loglinear Model Average				0.600	3.125
Sugar Beet Supply:					
Linear Models					
1	.2277533	24.87037	0.9129	0.583	0.755
2	.2328273	23.51467	0.9170	0.551	0.719
3	.2359719	10.23303	0.9062	0.240	0.314
4	.2641236	13.6813	0.9041	0.321	0.436
5	.1899675	13.73695	0.9222	0.847	1.046
6	.189804	14.45165	0.9234	0.891	1.100
7	.215316	11.67694	0.9220	0.720	0.918
8	.2070937	11.41112	0.9226	0.704	0.888
9	.2120759	11.42667	0.9239	0.705	0.894
Linear Model Average				0.618	0.786
Loglinear Models					
1	.5628604	2.546244	0.8419	2.546	5.825
2	.5472171	3.380183	0.8435	3.380	7.465
3	.5629378	1.127458	0.8292	1.127	2.580
4	.5438571	2.278983	0.8332	2.279	4.996
Loglinear Model Average				2.333	5.216

Note: For linear models, elasticities are computed at data means.