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The Value of Weather Information in Market Equilibrium

Bruce A. Babcock

Increased accuracy of weather forecasts does not necessarily increase commodity supply or farmer welfare. This study presents a stylized model of competitive production with rational expectations and demonstrates that improved weather information harms farmers facing an inelastic demand. Contrary to the conclusions of previous studies, the decline in farmer welfare does not require an expansion in expected supply. Better weather information may signal farmers to produce less on average under an inelastic demand. A supply decrease occurs when increases in the physical productivity of applied inputs are dominated by adverse price consequences.

Key words: market equilibrium, rational expectations, value of information, weather forecasts.

Widespread drought reinforces the notion that random weather processes can have both micro and macro effects on farmers. The productivity of farm inputs is affected as are output and input prices. Forecasts about weather, therefore, can affect the decisions of farmers in two ways: first, from the direct impact on physical productivity, and, second, through the profitability effects of expected price changes.

The impacts of weather forecasts on the physical productivity of input decisions are well studied (e.g., Byerlee and Anderson; Tice and Clouser; Rosegrant and Roumasset; Hashemi and Decker; Baquet, Halter, and Conklin; Stewart, Katz, and Murphy). However, the impacts of weather information on market prices have received little attention. One exception is Lave's analysis of the California raisin industry. He concludes that even a modest increase in supply from rainfall protection would lower total industry profits because of the inelastic demand for raisins. Thus, the raisin industry as a whole would be better off with less than perfect weather forecasts. However, Lave stopped short of examining how raisin producers would react to the knowledge that better weather forecasts lead to lower average prices. Presumably, the supply of raisins would decrease, thereby ameliorating

some of the adverse price effects.

Typically, the value of information to an individual producer is calculated as the difference between expected returns (or utility) using the information and expected returns without the information, with both expectations taken with respect to the more informed distribution. The aggregate value of information is the sum of the individuals' values. Both the individual and the aggregate value of information are nonnegative using this approach. Lave's analysis reveals the problem with calculating the value of information when the use of the information can lead to price effects. Such market effects cannot be captured by the usual method of calculating the value of information.

Farmers' reactions to the knowledge that the use of information will change output price depend on whether they act cooperatively or noncooperatively. Monopoly models can be used to examine how farmers will use information if they cooperate in setting output levels. Such collusive behavior may characterize decisions by farmers who grow crops covered by marketing orders that effectively control quantities, and hence, prices. However, most crops are not covered by marketing boards, and individual producers generally make their own supply decisions. Widely available information that is used by many producers can create a price externality (external to the control of individual producers). Models of noncooperative behavior must be used to capture these effects.

The purpose of this paper is to examine how

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the value of weather information is changed with improvements in the accuracy of forecasts when farmers act noncooperatively. Farmers are assumed risk-neutral, rational, and competitive. Further, each farmer is assumed to contribute a sufficiently small fraction of total output, so any individual's supply decision does not affect output price. Under these conditions better weather information could lead to a lower aggregate value of information. It is also shown, in contrast to Lave, that this result does not require an expansion in average supply.

The Model

Consider a competitive farmer with a crop yield which depends on the level of a controllable input, x, and an uncontrollable weather input, w, the level of which is known after x is applied. For simplicity, assume that w can only take on two values, w_g and w_b , and that the historical probability that w_g occurs is q. Denote the production function facing the farmer as

(1)
$$y = f(x, w), w = w_g \text{ or } w_b,$$

where y represents yield per acre. It is assumed that $f(x, w_g) > f(x, w_b)$ for all x.

To highlight the relationship between one region's weather forecast and output price, total supply is assumed to come from a single representative farmer. This farmer operates with the production function given by (1). In addition, this farmer is a risk-neutral price taker with rational expectations concerning output price. Although the demand function is nonstochastic, the price that the farmer will receive is stochastic before the weather variable is observed because of uncertain output. This formulation allows joint consideration of production and price uncertainty (Newbery and Stiglitz).

The assumption that the industry consists of one competitive producer with rational expectations is equivalent to assuming a large number of identical producers, none of which is large enough to affect output and each of which has rational expectations. The assumption of rational expectations means that each producer knows how the rest of the producers in the market will respond to changes in information, so the resulting distribution of output price is implied by the aggregate actions of all producers. No individual producer will find it profitable to diverge from what is optimal for all other pro-

ducers because the action of any single producer does not affect output price.

Suppose that the farmer receives a probability forecast about the future level of w when x is applied. Let ρ represent the forecasted probability that future weather will be w_g . Assume that the forecaster is "correct" in that w_g occurs 60% of the time when the forecaster says that the probability of receiving w_g is 60%. Assume that farmers adopt the forecasted probability as their own posterior probability. Let $g(\rho)$ denote the probability distribution function of ρ . The probability forecast ρ can take on any value between 0 and unity depending on observable weather conditions before the forecast is made and on the skill of the forecaster.

The farmer chooses the level of a variable input to apply after receiving a given forecast of future weather. The objective function and first-order condition for a specific value of ρ (e.g., $\rho = \rho_0$) are

$$\max_{x} E(\pi | \rho = \rho_{0}) = \rho_{0} P[f(x, w_{g})] f(x, w_{g})$$

$$+ (1 - \rho_{0}) P[f(x, w_{b})] f(x, w_{b}) - P_{x} x,$$

$$(2) \quad \rho_{0} P[f(x, w_{g})] f_{x}(x, w_{g})$$

$$+ (1 - \rho_{0}) P[f(x, w_{b})] f_{x}(x, w_{b}) - P_{x} = 0,$$

where $P(\cdot)$ is the demand function. Denote the solution to (2) as $x(\rho_0)$.

When choosing the level of x to apply, the farmer does not consider the change in output price implied by the level chosen because any single farmer faces a perfectly elastic demand curve. However, because the farmer uses all available information, the price distribution used to choose x in (2) is consistent with the choice of x. If this were not true, the farmer's choice would be suboptimal. Therefore, the derivative of output price with respect to input use does not appear in (2).

This concept of equilibrium naturally follows from the assumptions that no farmer is large enough to affect price and that farmers act non-cooperatively. Relaxing either of these assumptions would yield another type of equilibrium (Cornes and Sandler).

 $^{^1}$ This paper does not focus on how farmers process information; rather, it focuses on the effects of more reliable forecasts on the value of information. The translation of objective probabilities (data) into posterior probabilities with Bayes' rule would needlessly complicate the analysis. To give the analysis a more Bayesian interpretation, ρ can be considered a posterior probability formed by processing a signal from the weather forecaster, rather than a forecast itself. The results developed in the paper are applicable to either interpretation.

The value of weather information is given by

(3)
$$VI = \sum_{\rho} \{ \rho \pi[x(\rho), w_g] + (1 - \rho) \pi[x(\rho), w_b] - \rho \pi(x_h, w_g) - (1 - \rho) \pi(x_h, w_b) \} g(\rho),$$

where $\pi(\cdot)$ is the profit function for different forecasts, and x_h is the optimal amount of x employed using historical weather probabilities. Because x_h is not a function of ρ , the last two terms in (3) can be written

$$-\pi(x_h, w_o)\bar{\rho} - \pi(x_h, w_h)(1 - \bar{\rho}),$$

where $\bar{\rho} = \Sigma \rho g(\rho)$ measures the weighted sum of conditional probabilities that good weather will occur. Given the assumption of correct forecasts, $\bar{\rho} = q$.

Increases in forecast accuracy come about with fewer forecasts of ρ in the vicinity of q, and more around zero and one. Perfect forecasts are given by forecasts of $\rho = 1$, $q \cdot 100\%$ of the time, and $\rho = 0$ the rest. This probability framework closely follows that developed in Winkler, Murphy, and Katz.

To calculate the value of improved information requires a recalculation of VI for a new probability distribution of ρ . The value of improved information is the difference between VI under the old distribution and VI under the new distribution. The difference measures the change in an industry's willingness to pay for weather information given that the industry currently is basing its decisions on historical weather probabilities. Because q is invariant to the probability distribution of ρ , it is sufficient to look at

of weather information assuming that there are only two possible values for ρ . With probability c, $\rho = \rho_g$, and with probability 1 - c, $\rho = 1 - \rho_b$. A further restriction is placed on the relationship between ρ_g and ρ_b by the assumption that $\Sigma \rho g(\rho) = q$. The restriction is that

(4)
$$\rho_b = \frac{1 - c - q}{1 - c} + \frac{c}{1 - c} \rho_g.$$

Increases in forecast accuracy can be obtained by either increasing ρ_g or ρ_b . Assuming that c is held constant as forecast accuracy increases implies that for a given increase in ρ_g , a corresponding increase in ρ_b is defined by (4).

The value of weather information can now be written as

(5)
$$VI = c[\rho_g \pi(x_g, w_g) + (1 - \rho_g) \pi(x_g, w_b)] + (1 - c)[\rho_b \pi(x_b, w_b) + (1 - \rho_b) \pi(x_b, w_g)] - q \pi(x_h, w_g) - (1 - q) \pi(x_b, w_b),$$

where x_g and x_b are the optimal levels of x under the two values of ρ (ρ_g and $1 - \rho_b$).

Effects of an Increase in Forecast Accuracy

The value of information as defined in (5) is a function of forecast accuracy, which is represented by ρ_g . Because by (4), ρ_b is a function of ρ_g , changes in ρ_g affect both x_g and x_b . Differentiating the first-order condition (2) with respect to x and ρ (replacing ρ with its appropriate value) determines how input use changes as the forecasts become more accurate.

(6)
$$\frac{\partial x_g}{\partial \rho_g} = \frac{P[f(x_g, w_g)]f_x(x_g, w_g) - P[f(x_g, w_b)]f_x(x_g, w_b)}{-H_g},$$

(7)
$$\frac{\partial x_b}{\partial \rho_b} = \frac{P[f(x_b, w_b)]f_x(x_b, w_b) - P[f(x_b, w_g)]f_x(x_b, w_g)}{-H_b},$$

how expected profits of the information user change to gauge how the value of information changes as forecast accuracy increases (assuming that the forecasts remain correct).

The large number of possible values of ρ hampers a general qualitative exploration of the effects of increases in forecast accuracy. Restricting the number of possible forecasts increases the tractability of the problem. The remainder of the paper will focus on the effects

where H_g and H_b are the derivatives of (2) with respect to x_g and x_b . If demand is not upward sloping and if f is concave in x, both H_g and H_b are strictly negative.

How input demand changes as weather forecasts become more accurate depends on the relative magnitudes of output price and the mar-

 $^{^2}$ A forecast of $\rho = \rho_g$ can be considered a forecast of good weather. A forecast of $1 - \rho_b$ implies that the probability of w_b occurring equals ρ_b , so it can be considered a forecast of bad weather. Here good and bad weather refer only to output effects of weather.

ginal product of x under each of the weather states. By assumption, for a given level of x, $P[f(x, w_g)] < P[f(x, w_b)]$. Inputs x and w will be defined as production substitutes if $f_x(x, w_g) < f_x(x, w_b)$ and production complements if $f_x(x, w_g) > f_x(x, w_b)$.

Equation (6) can be unambiguously signed only when x and w are substitutes. When this occurs, both $P[f(x_g, w_g)] < P[f(x_g, w_b)]$ and $f_x(x_g, w_g) < f_x(x_g, w_b)$, so (6) is negative. When x and w are complements, the second inequality is reversed and (6) cannot be definitely signed. The condition for signing (7) is the same. When x and w are substitutes, $P[f(x_b, w_b)] > P[f(x_b, w_g)]$, $f_x(x_b, w_b) > f_x(x_b, w_g)$, and (7) is positive. Complementarity between x and w reverses the last inequality and the sign of (7) becomes indeterminant.

Signing (6) and (7) with complementarity between x and w depends on the responsiveness of output price to changes in supply and the degree to which the slope of the marginal product function of x is changed by weather. With a perfectly elastic demand curve, (6) is positive and (7) is negative. But if demand is quite inelastic, the negative price effects when good weather occurs are more likely to outweigh the positive productivity effects. The functional forms of the production and demand functions play a central role in determining how input use and supply change as weather forecasts become more accurate.

An exploration of necessary and sufficient conditions needed to sign the input, supply, and profit changes coming from improved weather information when w and x are complements proved quite fruitless. Instead, particular function forms are used to sign the effects. The forms used here assume that weather affects supply multiplicatively and that the demand function has constant elasticity. Let

(8)
$$f(x, w) = g(x)T(w) w = w_g \text{ or } w_b,$$

where $g_x > 0$ and $T(w_g) > T(w_b)$, represent the case of production complements. To focus on the elasticity of demand let

(9)
$$P[f(x, w)] = [f(x, w)]^{-\alpha},$$

where $\alpha > 0$. The (constant) elasticity of demand is $-\alpha^{-1}$. Using these functional forms, (6) and (7) become

(10)
$$\frac{\partial x_g}{\partial \rho_g} = \frac{-g_x}{g_{xx} - \alpha g^{-1} g_x^2} \cdot \frac{T(w_g)^{1-\alpha} - T(w_b)^{1-\alpha}}{\rho_g T(w_g)^{1-\alpha} + (1-\rho_g) T(w_b)^{1-\alpha}},$$

(11)
$$\frac{\partial x_b}{\partial \rho_b} = \frac{-g_x}{g_{xx} - \alpha g^{-1} g_x^2} \cdot \frac{T(w_b)^{1-\alpha} - T(w_g)^{1-\alpha}}{\rho_b T(w_b)^{1-\alpha} + (1-\rho_b) T(w_g)^{1-\alpha}}.$$

Given that $g_{xx} < 0$, the signs of (10) and (11) are determined by the value of α . When $\alpha < 1$ (i.e., demand is elastic)

$$T(w_p)^{1-\alpha} - T(w_b)^{1-\alpha} > 0,$$

which implies that

$$\frac{\partial x_g}{\partial \rho_a} > 0$$
 and $\frac{\partial x_b}{\partial \rho_b} < 0$.

The signs are reversed if demand is inelastic. Rewriting (5) as

$$VI = cE_{o}(\pi) + (1 - c)E_{b}(\pi) - E_{b}(\pi),$$

where the subscript on the expectations operator denotes the weather distribution used to maximize expected profits, shows clearly how to determine the marginal value of weather information as the information becomes more accurate. As noted above, changes in forecast accuracy do not change the *ex ante* expected profits of the farmer who does not use the information. The marginal value of better weather information, therefore, can be written as

(12)
$$\frac{\partial VI}{\partial \rho_g} = c \frac{\partial E_g(\pi)}{\partial \rho_g} + (1 - c) \frac{\partial E_b(\pi)}{\partial \rho_b} \frac{\partial \rho_b}{\partial \rho_g}$$
$$= c \left\{ \frac{\partial E_g(\pi)}{\partial \rho_g} + \frac{\partial E_b(\pi)}{\partial \rho_b} \right\}.$$

Applying the envelope theorem to the partial derivatives of the two profit functions results in

(13)
$$\frac{\partial E_{g}(\pi)}{\partial \rho_{g}} = P[f(x_{g}, w_{g})]f(x_{g}, w_{g}) - P[f(x_{g}, w_{b})]f(x_{g}, w_{b}) + [\rho_{g}f(x_{g}, w_{g})P'[f(x_{g}, w_{g})]f_{x}(x_{g}, w_{g}) + (1 - \rho_{g})f(x_{g}, w_{b})P'[f(x_{g}, w_{b})]f_{x}(x_{g}, w_{b})]\frac{\partial x_{g}}{\partial \rho_{g}}$$

(14)
$$\frac{\partial E_{b}(\pi)}{\partial \rho_{b}} = P[f(x_{b}, w_{b})]f(x_{b}, w_{b}) - P[f(x_{b}, w_{g})]f(x_{b}, w_{g}) + [\rho_{b}f(x_{b}, w_{b})P'[f(x_{b}, w_{b})]f_{x}(x_{b}, w_{b}) + (1 - \rho_{b})f(x_{b}, w_{g})P'[f(x_{b}, w_{g})]f_{x}(x_{b}, w_{g})] \frac{\partial x_{b}}{\partial \rho_{b}}$$

Determining the signs of (13) and (14) is straightforward. The first terms in the two expressions measure the expected profit effects from a change in expected weather.³ When demand is elastic (inelastic), revenue in the high output, low price state is greater (less) than the revenue in the low output, high price state. The second term measures the impacts on expected profits from the expected price change brought about by a different input use. Because demand is downward sloping, the sign of this effect is opposite the sign of the change in input use.

When demand is elastic and x and w are substitutes, (13) is positive and (14) is negative. The two effects work in the same direction for each equation. However, when demand is inelastic the signs cannot be determined unambiguously by simple inspection.

When x and w are complements and the two functional forms in (8) and (9) are appropriate, some algebraic manipulations and the substitution of (10) and (11) result in

$$\frac{\partial E_g(\pi)}{\partial \rho_g} = \frac{g^{1-\alpha}g_{xx}}{g_{xx} - \alpha g^{-1}g_x^2} [T(w_g)^{1-\alpha} - T(w_b)^{1-\alpha}]$$

$$\frac{\partial E_b(\pi)}{\partial \rho_b} = \frac{g^{1-\alpha}g_{xx}}{g_{xx} - \alpha g^{-1}g_x^2} [T(w_b)^{1-\alpha} - T(w_g)^{1-\alpha}].$$

When demand is elastic $(\alpha < 1)$, $T(w_g)^{1-\alpha} >$ $T(w_b)^{1-\alpha}$, so (15) is positive and (16) is negative. The signs are reversed when demand is in-

To sign (12) requires additional knowledge about the relative magnitudes of x_g and x_b . This is true even with the more restrictive functional

forms used to examine the changes when x and w are complements. To indicate what factors determine the sign of (12) when increases in wincrease the marginal product of x, let g(x) be a Cobb-Douglas function. That is, let

(17)
$$f(x, w) = Ax^{\beta} \cdot T(w) w = w_{\beta} \text{ or } w_{b},$$

with $T(w_g) > T(w_b)$. The remainder of the paper will utilize this particular functional form.

Changes in the Value of Information

Using (17), (12) becomes

(18)
$$\frac{\partial VI}{\partial \rho_g} = \frac{c(1-\beta)}{1-\beta(1-\alpha)} [T(w_g)^{1-\alpha} - T(w_b)^{1-\alpha}][g(x_g)^{1-\alpha} - g(x_b)^{1-\alpha}].$$

The sign of (18) depends on the relative magnitudes of x_e and x_b and on the elasticity of demand. The solutions to the first-order conditions with the production function in (17) are

(19)
$$x_g = K[\rho_g T(w_g)^{1-\alpha} + (1-\rho_g)T(w_b)^{1-\alpha}]^{1/1-\beta(1-\alpha)}$$
, and

(20)
$$x_b = K[\rho_b T(w_b)^{1-\alpha} + (1-\rho_b)T(w_g)^{1-\alpha}]^{1/1-\beta(1-\alpha)},$$

where

$$K = \left[\frac{\beta A^{1-\alpha}}{P_x}\right]^{1/1-\beta(1-\alpha)}.$$

The size of x_e relative to x_b is determined by the relative magnitudes of the two bracketed terms in (19) and (20) because $1 - \beta(1 - \alpha) > 0$. Noting that $\rho_{e} + \rho_{b} - 1 > 0$, which is the same as $\rho_g > q$ [see expression (4)], some straightforward algebra shows that the bracketed term in (19) is greater (less) than its (20) counterpart when demand is elastic (inelastic). Thus, $x_g >$ x_b when demand is elastic, and $x_g < x_b$ when demand is inelastic.

If demand is elastic, $g(x_g) > g(x_b)$, $g(x_g)^{1-\alpha} > g(x_b)^{1-\alpha}$, and $T(w_g)^{1-\alpha} > T(w_b)^{1-\alpha}$, which implies that the marginal value of information increases with an increase in forecast accuracy.

³ At first glance, one would think that the sum of the first two terms in expressions (13) and (14) must equal zero since the longrun or historical frequency of weather has not changed. But what has changed are the conditional probabilities of supply and price under each weather state. For example, given that w_g occurs, it is more likely that x_g will have been applied with an increase in ρ_g . Thus, with an elastic demand, expected supply, given that w_g occurs, increases. Similarly, it is more likely that x_b will have been applied when w_b occurs, so expected supply given w_b drops. The net effect is positive because, with x and w being complements, more output will be forthcoming in weather state w_g than is lost in

But, when demand is inelastic, the marginal value is negative. In this case, $T(w_g)^{1-\alpha} < T(w_b)^{1-\alpha}$, but because $x_g < x_b$, $g(x_g)^{1-\alpha}$ remains greater than $g(x_b)^{1-\alpha}$.

The decline in the value of weather information as information becomes more accurate appears to be a counterintuitive result. That is, it appears to violate the principle of optimality in which an action would not be taken if an individual is made worse off by the action. The argument here is different. Each farmer acts optimally by fully utilizing the weather information. Ignoring the information when all other farmers are using it would make a farmer worse off. Therefore, the value of improved information to an individual farmer is positive. The total industry may be worse off with better information because of negative price effects. If the industry could collectively decide on a position about the possibility of improving the accuracy of weather information, the decision would be to not make the improvement.

The result that agricultural producers facing an inelastic demand can be made worse off from better information is similar to the finding that average farmers who are forced to ride the technological treadmill by adopting new technologies can be made worse off (Wilcox and Cochrane). But, whereas this argument relies on a supply expansion to lower profits, it can be shown that aggregate farmer profits can decrease even when average supply decreases.

Changes in Input Use

First, consider how the average use of x changes as the weather forecast becomes more accurate. Define average use of x as

(21)
$$\frac{\partial \bar{x}}{\partial \rho_g} = c \left\{ \frac{\partial x_g}{\partial \rho_g} + \frac{\partial x_b}{\partial \rho_b} \right\}.$$

With x_g and x_b given by (19) and (20), expression (21) becomes

(22)
$$\frac{\partial \bar{x}}{\partial \rho_g} = \frac{cK}{1 - \beta(1 - \alpha)} \left[T(w_g)^{1 - \alpha} - T(w_b)^{1 - \alpha} \right] \left[R_1^{\phi} - R_2^{\phi} \right],$$

where $R_1 = \rho_g T(w_g)^{1-\alpha} + (1 - \rho_g) T(w_b)^{1-\alpha}$, $R_2 = \rho_b T(w_b)^{1-\alpha} + (1 - \rho_b) T(w_g)^{1-\alpha}$, and $\phi = \beta(1 - \rho_b) T(w_g)^{1-\alpha}$ $-\alpha$)/(1 - β (1 - α)), and K is as defined in (19). The first bracketed term in (22) is positive (negative) when demand is elastic (inelastic). The second bracketed term is always positive because an elastic demand makes $R_1 > R_2$ and ϕ > 0, while an inelastic demand makes $R_1 < R_2$ and $\phi < 0$. Thus, with an elastic demand curve, average use of x increases with increases in forecast accuracy. In contrast, average use of x declines if demand is inelastic. The latter case illustrates that more accurate weather forecasts can signal farmers that, on average, it is more profitable to use less of the supply-increasing input. The consequences of this signal on expected supply are shown next.

Changes in Expected Supply

Expected supply is given by

$$E(y) = cg(x_g)[\rho_g T(w_g) + (1 - \rho_g)T(w_b)] + (1 - c)g(x_b)[\rho_b T(w_b) + (1 - \rho_b)T(w_g)].$$

An increase in forecast accuracy can be evaluated by differentiating expected supply with respect to ρ_g , which with g(x) specified as Cobb-Douglas results in

$$(23) \quad \frac{\partial E(y)}{\partial \rho_g} = c[g(x_g) - g(x_b)][(T(w_g) - T(w_b)]$$

$$+ cK_2 \left[g(x_g) \frac{\rho_g T(w_g) + (1 - \rho_g) T(w_b)}{\rho_g T(w_g)^{1-\alpha} + (1 - \rho_g) T(w_b)^{1-\alpha}} - g(x_b) \frac{\rho_b T(w_b) + (1 - \rho_b) T(w_g)}{\rho_b T(w_b)^{1-\alpha} + (1 - \rho_b) T(w_g)^{1-\alpha}} \right],$$

where

$$K_2 = \frac{c\beta}{1 - \beta(1 - \alpha)} A \left[\frac{\beta A^{1-\alpha}}{P_x} \right]^{\beta/1 - \beta(1-\alpha)} \cdot [T(w_g)^{1-\alpha} - T(w_b)^{1-\alpha}].$$

$$\bar{x} = cx_{\varrho} + (1 - c)x_{\varrho}.$$

The change in average use of x due to an increase in ρ_g then is written,

The sign of (23) is not immediately apparent. It can be shown, however, (see the appendix) that when demand is inelastic, (23) is negative. Moreover, a sufficient condition for expected

supply to increase when demand is elastic is $\beta(2)$ $-\alpha$) - 1 > 0.

A Numerical Example

The intuition behind the qualitative results developed above can be obtained with the use of a simple numerical example. Assume that ρ_g = $\rho_b, c = q = 0.5, \text{ and } T(w) = 1 + w, \text{ with } w_g$ = .2, and $w_b = -.2$. The Cobb-Douglas portion of the production function is defined by setting $\beta = 0.5$ and A = 2. With this model specification, the calculated changes in ex ante expected profits, output, price, and input use as ρ increases from .5 (no information) to unity (perfect information) for both an elastic and an inelastic demand are presented in table 1. Demand is given by expression (9). Average use of x, expected supply, and expected profits all increase (decrease) as forecast accuracy increases when demand is elastic (inelastic). The response of expected profits is seen by noting that expected price also increases (decreases) as forecast accuracy increases when demand is elastic (inelastic).

To see what drives these results, refer to table 2, which reports the input levels and corresponding output levels under the two weather forecasts and the two weather states. Also reported in table 2 are expected output levels conditional on weather for the two demand elasticities. Conditional expected output is E(y|w) = w_g) = $\rho f(x_g, w_g) + (1 - \rho) f(x_b, w_g)$, under w_g , and $E(y|w = w_b) = \rho f(x_b, w_b) + (1 - \rho) f(x_g)$ w_b), under w_b where $f(\cdot)$ denotes the production function. When $\rho = .5$, $x_{e} = x_{b}$, and the only variability in output is due to weather variation, which implies that $E(y|w=w_g)=f(x_g,w_g)$. When $\rho = 1$, there is no weather uncertainty, and again, $E(y|w = w_g) = f(x_g, w_g)$ because the probability associated with $f(x_b, w_g)$ is zero. Similarly, E(y|w)

Unconditional Expected Effects of Weather Information Table 1.

Forecast accuracy (ρ)	Demand Elasticity									
	-5.0				-0.5					
	0.5	0.7	0.9	1.0	0.5	0.7	0.9	1.0		
Input use $(E(x))$ Supply $(E(y))$	4.580 2.140	4.591 2.149	4.622 2.174	4.646 2.194	1.893 1.375	1.891 1.372	1.887 1.360	1.884 1.351		
Price $(E(P))$	0.863	0.864	0.865	0.866	0.596	0.593	0.585	0.578		
Profits $(E(\pi))$	0.916	0.918	0.924	0.929	0.379	0.378	0.377	0.376		

Table 2. Conditional Effects on Input and Output Levels of Weather Information

Weather Forecast	Good Weather ^a				Bad Weather					
	Demand Elasticity = -5.0									
Forecast accuracy (ρ)	0.5	0.7	0.9	1.0	0.5	0.7	0.9	1.0		
Input use	4.58	5.08	5.60	5.87	4.58	4.10	3.64	3.42		
Realized output under										
good weather	2.57	2.71	2.84	2.91	2.57	2.43	2.29	2.22		
bad weather	1.71	1.80	1.89	1.91	1.71	1.62	1.53	1.48		
Expected output given										
good weather	2.57	2.63	2.79	2.91						
bad weather	1.71	1.67	1.57	1.48						
	Demand Elasticity = -0.5									
Input use	1.89	1.79	1.69	1.63	1.89	1.99	2.09	2.14		
Realized output under										
good weather	1.65	1.61	1.56	1.53	1.65	1.69	1.73	1.75		
bad weather	1.10	1.07	1.04	1.02	1.10	1.13	1.16	1.17		
Expected output given										
good weather	1.65	1.63	1.57	1.53						
bad weather	1.10	1.11	1.15	1.17						

^a Good weather is represented by w_g , and bad weather is represented by w_b . A forecast of good weather occurs when $Pr(w = w_g) = \rho$. A forecast of bad weather occurs when $Pr(w = w_g) = 1 - \rho$.

 $= w_b$) = $f(x_b, w_b)$ under the two information extremes.

The implications of the behavior of these conditional output expectations can be seen in figure 1, which depicts the unconditional expected output and price for $\rho = .5$ and unity under an inelastic demand. In figure 1, y_g^p denotes output under perfect information and good weather; y_g^n , output under no information and good weather; y_b^p , output under perfect information and bad weather; and y_b^n , output under no information and bad weather. Furthermore, let P_g^p , P_g^n , P_b^p , and P_b^n denote the corresponding prices. Under the assumption that q = 0.5 (the two weather states have an equal chance of occurring), unconditional expected price and output are found by bisecting the rays connecting the two output/ price pairs under each of the two weather information extremes. As shown in figure 1, as ρ increases from 0.5 to unity, expected output decreases from $E^n(y)$ to $E^p(y)$ and expected price decreases from $E^n(P)$ to $E^p(P)$. Unconditional expected revenue declines because both expected output and expected price decrease. This decline more than offsets the decrease in expected cost, hence expected profits decline.

places y_b^i and $E(y|w=w_b)$ replaces y_b^i , i=p or n.

The results reported in table 2 also illustrate the relationship between demand elasticity and supply variability. With an inelastic demand improvements in information reduce output variability. Farmers produce less when they are more confident that good weather is forthcoming and more when they are more confident that bad weather is forthcoming. With an elastic demand increases in forecast accuracy increase output variability because farmers are primarily concerned with the physical productivity effects of weather rather than the price effects. Thus, even though improvements in forecast accuracy decrease uncertainty, supply and price variability may increase.

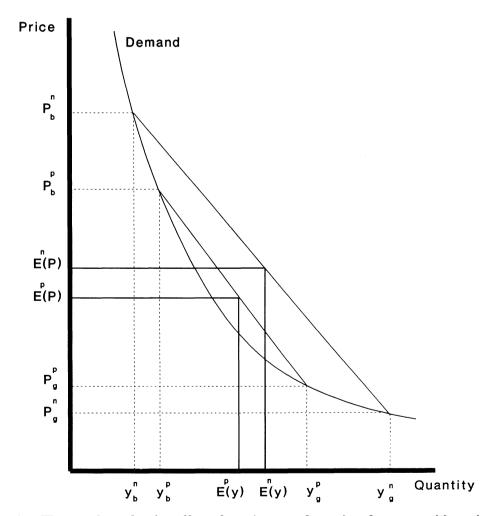


Figure 1. The supply and price effects from improved weather forecasts with an inelastic demand

⁴ It can be shown that the relationship between E(y|w) and ρ is monotonic for both weather states. Thus, the situation depicted in figure 1 holds for all values of ρ if, in figure 1, $E(y|w=w_g)$ replaces ψ , and $E(y|w=w_g)$ replaces ψ , if $E(y|w=w_g)$ replaces ψ , and $E(y|w=w_g)$ replaces ψ .

Other simulation results involving a quadratic production function and a linear demand curve give further insight into the use of weather information. There were two major differences between those results and the ones reported here. First, the physical productivity effects of weather information always dominated the price effects: when good weather was forecast more accurately, more of the supply-increasing input was used; when bad weather was forecast more accurately, less of the input was used. The net effect was that expected supply increased for both inelastic and elastic demands. The second difference was that expected price and expected supply moved in opposite directions because of the restrictions imposed by the linear demand curve. Therefore, with an inelastic demand, the expected supply increase from improved weather forecasts resulted in lower total revenue, which, when combined with higher costs, meant that expected profits decreased with improvements in weather forecasts. With an elastic demand, the expected supply increase caused total revenues to increase, which more than dominated the increase in cost. Thus, the basic result that better weather information can lead to lower producer welfare is not dependent on the functional forms used here. However, the changes in input use and expected supply from better weather information are much more dependent on the particular interactions between weather variables and the marginal products of production factors.

Concluding Comments

Information is generally considered to be a supply-increasing production input and welfare increasing to producers. The argument is that producers would not use information if it did not make them better off. These two well-accepted characterizations are valid if there are no price effects from the use of the information.

Optimal input use is not only a function of physical productivity, it also depends on prices. If information signals farmers that prices will be much lower, for example, then it may be optimal to reduce the use of production factors. Price changes can also influence the value of information. The definitional truism that information is welfare increasing presumes no external effects from the use of information. One source of possible external effect is from prices. Information about the productivity of input decisions will influence prices if enough producers utilize the information to make their supply decisions. Competitive farmers have no control over prices. This lack of control creates a price externality: the aggregate effects of farmers' actions change prices, but individual farmers are too small to have a significant effect; hence, the marginal price effects are not taken into account when production decisions are made.

This paper examines an agricultural industry with many identical producers, all of whom control supply with a single variable production input. From this model, it is shown that the role of information in a production system can be quite different than is generally considered. Lave's result that producers can be made worse off from better weather information is shown to be true even when farmers know that their collective action is making them worse off. Moreover, market price effects from information can dominate physical productivity effects, particularly when demand is inelastic. When this occurs, information is a supply-decreasing production input: more accurate information signals farmers that it is more profitable for them to produce less, not more.

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Appendix

Proof of Negativity

The proof that equation (23) is negative with an inelastic demand curve is straightforward. First, note that because $x_{g} < x_{b}$ with an inelastic demand, the first term of (23) is negative. Also note that K_{2} in (23) is negative with an inelastic demand curve. All that remains to be shown is that the bracketed term following K_{2} in (23) is positive with an inelastic demand. After substituting the analytic solutions for x_{g} and x_{b} [equations (19) and (20)] into (23), the term in question be rewritten as

$$(A1) K_3 R_1^{\gamma} - K_4 R_2^{\gamma},$$

where $K_3 = \rho_g T(w_g) + (1-\rho_g) T(w_b)$; $K_4 = \rho_b T(w_b) + (1-\rho_b) T(w_g)$; $R_1 = \rho_g T(w_g)^{1-\alpha} + (1-\rho_g) T(w)^{1-\alpha}$; $R_2 = \rho_b T(w_b)^{1-\alpha} + (1-\rho_b) T(w_g)^{1-\alpha}$; and $\gamma = [\beta(2-\alpha)-1]/[1-\beta(1-\alpha)]$. K_3 is greater than K_4 , by the assumptions that $w_g > w_b$ and $\rho_g + \rho_b > 1$. With an inelastic demand, $R_1 < R_2$. The exponent γ is negative with $\alpha > 1$ by the assumption that $\beta < 1$. Hence, (A1) is positive. The proof is complete.