Appendix: Modeling the Value of Information

Information has value to the extent that it helps individuals and firms make better decisions. Currently, an improved SBR forecast allows farmers to make SBR management decisions more suited to the actual SBR situation. The more accurate the forecast, the more decisions can be fine-tuned to the situation and the less likely farmers will be to make management decisions that turn out to be suboptimal—that is, the less likely they will be to spray fungicides when SBR is not a threat and not spray fungicides when SBR does occur. This appendix provides a detailed description of how we formalized a concept of the value of SBR information and arrived at the estimates described in the body of the report.

Our approach to valuing information has broad theoretical underpinnings in the literature on Bayesian decisionmaking. Our updating mechanism is necessarily more rudimentary than commonly applied because of the rough data available on farmer's prior and posterior probabilities of infection. For more background, Lindley reviews the basic concepts underlying the value of information in decision science. Lawrence provides a number of applications of the basic theory. The edited volume by Katz and Murphy examines the value of weather forecasts and includes analyses that use methods similar to the one presented here.

The most crucial assumption in assessing the value of information concerns the quality of the information provided. In this context, information quality pertains to the accuracy of the SBR forecast implicit in information provided by the framework. The more accurate the forecast affecting farmers' prior belief about the probability of infection, the more it affects farmers' SBR management decisions and the less likely farmers will be to regret their management decisions at harvest time. Unfortunately, information quality is also the most difficult feature to objectively quantify. Our solution to this quandary is to estimate information values for a range of information qualities.

The Conceptual Framework

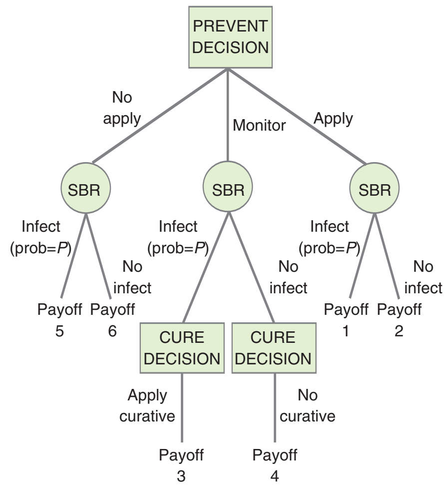
To estimate the value of information, we evaluate farmers' profit-maximizing management decisions with and without information from the framework and estimate the difference in expected profits. In our base case, this difference in expected profits is the economic value of information. In the other cases, the concept is similar but with some additional features.

SBR Management and Expected Profit Without the Framework

We first consider farmers' optimal management strategies and expected profits without the benefit of information from the framework. Our analysis assumes that farmers have three possible management strategies: (1) apply a preventative fungicide before SBR occurs; (2) intensively monitor fields and then apply a curative fungicide if SBR occurs; or (3) do nothing—that is, manage soybean fields as if SBR were not a potential threat. Any given farmer's profit-maximizing decision depends on the costs of preventative and curative fungicides, monitoring costs, yield losses in the event of an SBR infection for each management strategy, soybean prices, and farmers' perceived likelihood that an SBR infection will occur. These assumptions were described in the body of the report and a more detailed description of how we arrived at these assumptions is given below.

Appendix figure 1 shows how the three strategies lead to six possible outcomes, depending on farmers' strategies and whether or not an SBR infection actually arises on their farm. These six possible outcomes were given in table 2 and are labeled in the figure as Payoffs 1-6.

Appendix figure 1
Decision tree without information about SBR infection



The six payoffs embody the costs and benefits of each strategy. The first strategy (preventative fungicide) has the benefit of minimizing yield losses in the event of an SBR infection but at a high per acre cost of fungicides. The second strategy (monitor fields and apply a curative fungicide if SBR is detected) costs less per acre than the preventative treatment but results in larger yield losses in the event of SBR. It also saves fungicide costs in the event SBR does not occur. The third strategy (do nothing) is the least costly alternative but results in the largest yield losses in the event of an SBR infection.

We assume farmers choose the strategy that maximizes their expected profits. For each strategy, expected profits equal the sum of the probabilities of each possible outcome multiplied by the associated payoffs. Each strategy has just two possible outcomes, one occurring with probability P (in the event SBR occurs) and one occurring with probability $1-P$ (in the event SBR does not occur). Thus, the expected profits for the three strategies are as follows:

Strategy	***Expected profits***
Preventative treatment:	$P \times$ Payoff 1 + $(1-P) \times$ Payoff 2
Monitor-curative if SBR:	$P \times$ Payoff 3 + $(1-P) \times$ Payoff 4
Nothing:	$P \times$ Payoff 5 + $(1-P) \times$ Payoff 6

Decisions may differ among farmers, depending on differences in the payoffs and farmers' beliefs about P. Parameter P represents farmers' *prior beliefs*, as described in the body of the report. The prior belief is a subjective probability—what a farmer believes the probability of infection to be given his or her prior knowledge and information. This subjective view of probability is also called the Bayesian view of probability. The Bayesian view of probability contrasts with the Frequentist view of probability, which holds that probabilities are objective, fixed values that are unknowable to human observers. Under the Frequentist view, expected values and information values cannot be calculated because the true probabilities that enter these calculations are not knowable. In this analysis, we assume farmers are rational economic actors with prior beliefs that are correct—that is, prior beliefs are the true probabilities.

For the base case scenario, we consider a representative farmer in each region and assume (implicitly) that all farmers within each region choose the same strategy—that is, they have the same prior beliefs. The six payoffs are constructed using the assumptions presented in table 1 and described later in more detail.

Given our assumptions about the six payoffs, farmers' optimal strategies and resulting expected profits crucially depend on *P*. In general, farmers will tend to apply a more costly management strategy the greater the probability of infection. If *P* is low (e.g., below 0.19 in the Corn Belt), the optimal strategy is to do nothing. In a broad intermediate range (e.g., for *P*, 0.19-0.62 in the Corn Belt), the optimal strategy is to monitor fields intensively and spray a curative fungicide if SBR arises. If *P* is sufficiently high (e.g., above 0.62 in the Corn Belt), the optimal strategy is to apply the preventative fungicide. Assumptions about farmers' prior beliefs in the base case, illustrated in figure 3, are based on an aerobiology analysis of SBR and wheat stem rust. Derivation of these probabilities is described later in more detail.

Note that if farmers knew *for certain* whether or not SBR would occur (P=0 or P=1), the optimal strategy in all regions would be to apply the preventative treatment if SBR were going to occur and do nothing if SBR were not going to occur. With known SBR occurrence, a monitor and cure strategy would never be optimal. In contrast, given our estimated values for *P*, the optimal strategy in all regions in the absence of any information is to monitor fields and apply the curative fungicide in the event SBR occurs. This difference in optimal strategies with and without information allows us to value the information.

SBR Management and Expected Profit With the Framework

We just considered farmers' SBR management strategies and expected profits in the hypothetical context where the coordinated framework did not exist. Now, we consider farmers' optimal strategies and expected profits in the observed situation where farmers can obtain information about the incidence of SBR via the framework. In this context, farmers choose their management strategies after learning about the incidence of SBR in their area.

We illustrate this environment by using the decision tree in appendix figure 2. This figure differs from appendix figure 1 in that farmers receive a "high-risk" or "low-risk" signal before choosing their management strategy. The two segments of the tree that follow each of these signals are much like the no-information tree in appendix figure 1, except the probability of infection is now β if the farmer receives a "high-risk" signal and γ if the farmer receives a "low-risk" signal. If the information signal provides a useful forecast, then $\beta > P$ and $\gamma < P$; that is, the "high-risk" signal increases the farmer's perceived risk of SBR and the "low-risk" signal reduces the farmer's perceived risk of SBR. Thus, unlike the no-information environment, here farmers may fine-tune their management strategies to the risk signal they receive and maximize expected profits *conditional* on the risk signal.

Thus, conditional on the risk signal, expected profits for the three strategies are as follows:

If "high-risk" signal,

Strategy	***Expected profits***
Preventative treatment:	$\beta \times$ Payoff 1 + $(1-\beta) \times$ Payoff 2
Monitor-curative if SBR:	$\beta \times$ Payoff 3 + $(1-\beta) \times$ Payoff 4
Nothing:	$\beta \times$ Payoff 5 + $(1-\beta) \times$ Payoff 6

If "low-risk" signal,

Strategy	***Expected profits***
Preventative treatment:	$\gamma \times$ Payoff 1 + $(1-\gamma) \times$ Payoff 2
Monitor-curative if SBR:	$\gamma \times$ Payoff 3 + $(1-\gamma) \times$ Payoff 4
Nothing:	$\gamma \times$ Payoff 5 + $(1-\gamma) \times$ Payoff 6

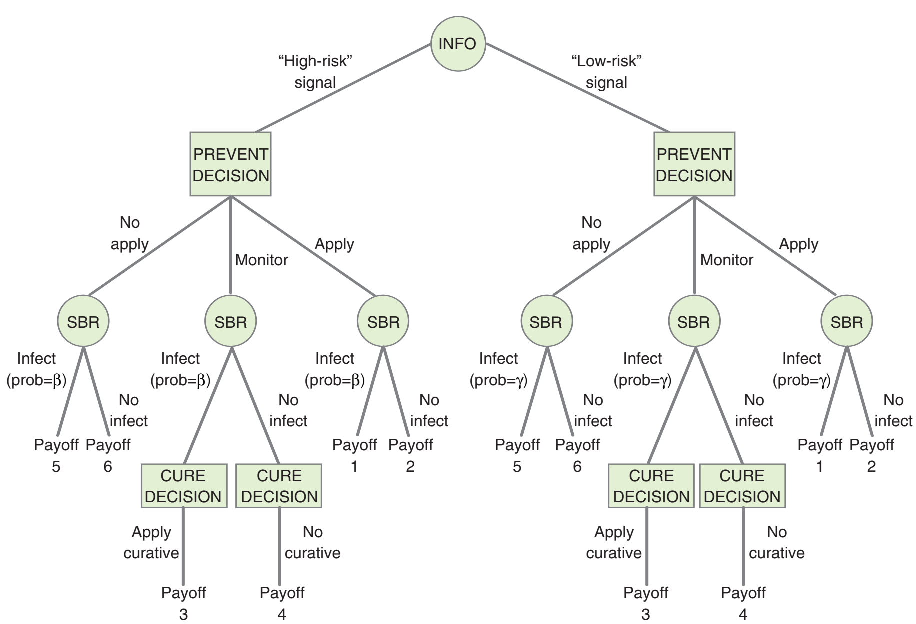
To calculate overall expected profits, we sum the expected profits from the optimal strategy conditional on each signal multiplied by the probability of receiving each signal. The probability of a "high-risk" signal is denoted by α, and the probability of a "low-risk" signal is given by $(1-\alpha)$. Thus, with information, expected profits are as follows:

$\alpha \times$ "high-risk" expected profit + $(1-\alpha) \times$ "low-risk" expected profit

Probabilities in this environment are logically connected to the prior belief P in the no-information environment. This connection comes from the fact that the information provided by the framework does not change the overall chance that an SBR infection will occur, only farmers' knowledge about whether it will occur. Mathematically, this connection requires that $P = \alpha \times \beta + (1-\alpha) \times \gamma$.

Appendix figure 2

Decision tree with partial information about SBR infection



Information Quality

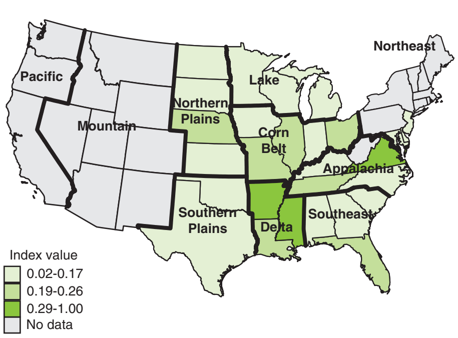
In general, one might quantify information quality in many ways. We have simplified matters considerably by assuming that the framework will provide just two possible information signals, “high-risk” and “low-risk.” In reality, the framework may provide a continuum of possible signals. If information quality were perfect, however, we would expect only two signals, one perfectly forecasting an impending arrival of SBR and one perfectly forecasting the nonarrival of SBR—that is, β would equal 1 and γ would equal zero. To approximate a continuum of information qualities, we, therefore, suppose just two signals remain but that the signal itself may have different levels of accuracy. Thus, if neither of the two signals contain informational content, they would not affect farmer’s prior beliefs (P=β =γ), and farmers would choose the same management strategy in the information environment as they would in the no-information environment.

To develop an index of information quality, we calculate a regional index of support from the coordinated framework from survey results provided to us by the Government Accountability Office (app. fig. 3). The survey also helped us develop the previous discussion of the framework’s operation. An index of support is calculated from the number of sentinel plots and rust extension agents in each State. When we consider this map along with the prior beliefs probability map, we find that farmers in some States clearly have high prior beliefs and low support (Alabama, Georgia, North and South Carolina, and Texas) and vice versa (Arkansas).

In making these calculations, we find that, while the index of support might represent regional differences in data collection for the framework, it did not reliably portray regional differences in how accurate producers would find the information to be. The quality of the information to soybean producers would depend on access, timeliness, and interpretation at the local level. To develop an operational index of information quality, we assume both information signals affect prior beliefs (P) by the same proportion. Mathematically, we suppose $\beta = \phi(1-P) + P$ and $\gamma = P(1-\phi)$, where ϕ is the information quality index that may take on any value between 0 and 1. This parameterization implies that, when $\phi = 0$, $P = \beta = \gamma$, and as ϕ increases, β increases and γ declines until $\phi = 1$, when $\beta = 1$ and $\gamma = 0$. This parameterization also implies $\alpha = P$: The probability of a “high-risk” signal always equals the probability that an infection will occur. Note, however, that a “high-risk” signal does *not* imply that an infection will occur for certain, unless $\phi = 1$.

Because we do not have objective estimates for information quality, we evaluate farmers’ optimal conditional strategies and expected profits over a range of information qualities: $\phi = 0.2$ (low), $\phi = 0.5$ (medium), and $\phi = 0.8$ (high). One may

Appendix figure 3
Coordinated framework index of support in USDA production regions



think of these information qualities as the proportion of uncertainty resolved by the coordinated framework. We then calculate farmers' overall expected profits by multiplying the conditional expected profits by the probabilities of each signal and summing them.

The Value of Information

In the base case scenarios, the value of information simply equals the difference in expected profits between the no-information and partial-information environments, calculated as we just described. These values, calculated for each region and each information quality, are reported in appendix table 2. In appendix table 1 and figure 3, we report information values for the Corn Belt over the full range of possible values for *P*, rather than our estimated *P* (described later) to show how sensitive our results might be to a range of values of *P*.

Assumptions

This section describes how we arrived at the assumptions used to develop estimates of the six payoffs and prior beliefs (*P*) for each region.

Soybean Yield Impacts

Yield data, before and after the arrival of *P. pachyrhizi*, are not available for the United States, nor are efficacy trial data for U.S. fungicides. Efficacy data also were not available at the time of this study for climatic regions similar to the United States. Thus, to estimate treated and untreated yield impacts of SBR epidemics relative to rust-free yields, we evaluate the impacts of rust on soybean yields in South America.

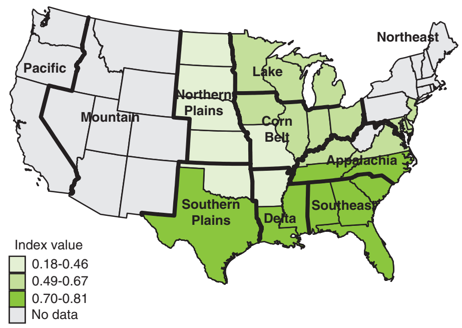
Livingston et al. analyzed fungicide efficacy trials in Brazil and Paraguay during 2001-03, aggregate yield data for 10 states in Brazil during 1993-2002, and data on the introduction of *P. pachyrhizi* into those same states. Rust-free yields averaged 2.604 (±0.422) metric tons per hectare, and treated and untreated yields averaged 2.578 (±0.201) and 2.025 (±0.363) metric tons per hectare. Treated and untreated yields, therefore, were lower by an average of 4.3 percent (±5.2 percent) and 25.0 percent (±11.9 percent), respectively, than the estimated rust-free yields.

We use the Livingston et al. estimate of untreated yield impacts to estimate payoffs when rust occurs but no fungicide is applied. Because the treated yield impacts from the Livingston et al. study were estimated with yield data reported from soybean plots sprayed with curative, protectant, or curative plus protectant fungicides, we need to separate the impacts of the different treatments. Replicating the Livingston et al. methods, we find that the average yield impact for the protectant class of fungicides is -0.97 percent with a mean of 1.00 applications evaluated. Fourteen protectant fungicide efficacy trials were conducted, each of which evaluated the impact of one application. Also, the average yield impact for the curative class of fungicides is -6.95 percent with a mean of 1.39 applications evaluated. Seven curative fungicide efficacy trials evaluated the impact of 2 applications, and 11 curative fungicide efficacy trials evaluated the impact of 1 application (app. table 7).

Prior Probabilities of Soybean Rust Occurring

Soybean producers in different regions are likely to assign different probabilities to the chance of rust occurring in their area (earlier denoted as *P*) (app. fig. 4). We call these probabilities "prior probabilities" and assume that they depend on regional differences in climate, soybean planting dates, and distance from *P. pachyrhizi* overwintering sites.

Appendix figure 4
Prior probability of soybean rust in USDA production regions



Wheat is the only other crop for which we have U.S. rust infection data. We, therefore, use data on the occurrence of stem rust epidemics of durum, winter, and other spring wheat for 1921-62 (Hamilton and Stakman) to estimate how often *P. pachyrhizi* spores may be present in most States where soybeans are produced (USDA, 2005a). We also use data on daily temperature extremes, rainfall, and humidity for 1992-2001 to estimate the proportion of years conditions may favor the development of soybean rust in each State (Livingston et al.). Because *P. pachyrhizi* may be able to overwinter along the coastlines of Alabama, Florida, Georgia, Louisiana, Mississippi, and Texas (Pivonia and Yang), we set the proportion of years that climatic conditions may favor the development of soybean rust to 1 for these States. *P. pachyrhizi* cannot survive without a plant host. We, thus, use data on the most likely soybean planting and harvest dates for each State (USDA, 1997) to adjust the proportion of years climatic conditions may favor rust epidemics.

We use the product of the proportion of years that stem rust epidemics occurred and the adjusted proportion of years climates may favor the development of rust epidemics to estimate State-level prior probabilities that rust epidemics may occur. To obtain regional prior probabilities, we weighted the State-level prior probabilities by mean soybean production for 1995-2004 (USDA, 1998-2005). Our estimate of the prior probability that the average U.S. soybean acre experiences rust is 0.53; and our estimates of the regional prior probabilities for Appalachia, Corn Belt, Delta, Lake States, Northeast, Northern Plains, Southeast, and the Southern Plains are 0.67, 0.55, 0.55, 0.49, 0.62, 0.43, 0.76, and 0.51, respectively. These are the estimates we used to calculate information value in the base case and other scenarios.

Summary Statistics About Representative Soybean Farms

We calculate estimates of the value of information per farm for farms having 443-1,956 acres of soybeans, depending on the region (app. table 6). We determine the acreage by estimating the weighted average of farms by soybean acre in each region. We weight farms by soybean acreage in order to represent the average soybean acre rather than the average farm. Weighting farms in this way is important because farms are extremely heterogeneous, with most producing little or no soybeans and smaller numbers producing vast soybean acreages. We estimate the base wealth used in the analysis of risk-averse farmers (see next section) by weighting farm households' net worth by soybean acre.

Note that the acreages of the representative farms affect only information values for the representative farm, not the estimated values per acre. The base wealth estimates affect only information values in the analysis of risk-averse farmers.

The data used to construct these averages come from the 2003 Agricultural Resource Management Survey. The sample design of the survey is complex; it samples farms of different sizes with different frequencies (see http://www.ers.usda.gov/briefing/ARMS/). The regional averages also incorporate sample weights implied by the survey design.

Modeling Information Values of Risk-Averse Farmers

Estimated information values for risk-averse farmers assume that farmers have diminishing marginal utility of wealth, which means that farmers value each additional dollar less than dollars already possessed (app. table 3). Diminishing marginal utility of wealth is characterized as risk aversion because it implies a constant level of wealth is preferred to variable levels of wealth with the same average value.

More specifically, our estimates of information values in the case of risk aversion assume that farmers' preferences are characterized by constant relative risk aversion (CRRA), with a coefficient of relative risk aversion equal to 4. This may be expressed with the utility function: $u(W) = -AW^{-3}/3$, where W indicates wealth and A is an arbitrary constant.

The utility function implies that farmers are strongly risk averse. We made this assumption to throw into stark relief the potential impact of risk aversion. More realistic assumptions about the level of risk aversion would imply even smaller differences from the base case. The extremity of our assumption may be observed by noting that a farmer with this utility function and a wealth of $200,000 values an additional dollar 16 times as much as the same farmer with a wealth of $400,000 and 625 times as much as the farmer with a wealth of $1 million. Farmers with less risk aversion would have information values closer to the base case, holding all else the same.

Calculating information values for risk-averse farmers' proceeds similarly to the base case described earlier, except that farmers are assumed to maximize *expected utility* rather than *expected profits*. In only a few cases does the extreme level of risk aversion cause farmers' decisions to be different than those in the base case. It changes information values, however, mainly because different information environments may lead to marked differences in profit variability. For example, consider a farmer who would have applied the preventative strategy without information. Suppose that if armed with a high-quality SBR forecast, the farmer splits his or her decision between prevention and "do nothing" across the "high-risk" and "low-risk" signals. The information would cause his or her average profits to increase but would also cause his or her profit variability to increase, so the information would be valued less by risk-averse farmers than by profit-maximizing farmers. This example illustrates the main reason that the largest information values decline in the risk-averse scenarios compared with the base case.

Modeling the Effect of Price Feedback on Information Values

In the base case scenarios, we assume that soybean prices are constant. However, both economic theory and our historical evidence indicate that soybean prices will vary with yield, implying that, because each decision (prevent, monitor/cure, or no management) and each outcome (rust infection, no rust infection) lead to a different yield, each must also lead to a different post-harvest price. Appendix table 4 reports information values that result from taking these soybean price effects into account, rather than assuming that prices are constant. This section explains how these values are calculated.

Equilibrium in the Soybean Market

The soybean futures price must reflect a possible variety of post-harvest prices. Specifically, the futures price must equal the average of these potential end-of-season prices, weighted by the probabilities that they will occur, which in the case where no information is available, means the following:

Prob (*SBR infection*) × (*Post-harvest price w/SBR infection*) +
Prob (*no infection*) × (*Post-harvest price w/o infection*) = *Futures price*.

With partial information, this condition becomes the following:

Prob (*infection and "high risk" signal*) × (*Post-harvest price w/infection and "high risk" signal*) + Prob (*infection and "low risk" signal*) × (*Post-harvest price w/infection and "low risk" signal*) +
Prob (*no infection*) × (*Post-harvest price w/o infection*) = *Futures price*.

Many factors can influence futures prices, but the following is how we assume that rust might affect futures prices. Underlying the equations are two concepts: Prices affect farmer treatment decisions, and farmer treatment decisions simultaneously affect prices. These circular effects must be taken into account when looking for equilibrium in the soybean market. Specifically, equilibrium should be characterized as follows: Individual farmers, taking post-harvest prices as given, maximize their own profits, while the industry as a whole, comprised of these individual profit-maximizing farmers, satisfies the equations, thus determining post-harvest prices.

In computing the equilibria seen in appendix table 4, we look wherever possible for symmetric, pure-strategy equilibria—pure strategy meaning that each farmer pursues a single best option, and symmetric meaning that, for all farmers, the best option is the same. In two cases, however, such equilibria do not exist. For the Northern Plains receiving information quality of 0.5 and for the Southern Plains receiving information quality of 0.2, we are forced to consider the potential for farmers to mix strategies. (An example of a mixed strategy would be tossing a coin and applying preventive fungicide if it came up heads and doing nothing if it came up tails.) Mixing strategies will occur only when individuals are indifferent to the two options; in these two cases, farmers are indifferent between monitoring and no management when they receive a low-risk signal. An equilibrium will result in the Northern Plains scenario when, in response to a low-risk signal, about 35 percent of acreage is monitored; the remainder is unmanaged; and the post-harvest price, when the signal indicates low risk but infection occurs anyway, is $6.91. Similarly, the Southern Plains will reach equilibrium when, in the face of low risk, about 27 percent of acreage is monitored; 73 percent is unmanaged; and the post-harvest price, when the signal indicates a low risk signal but infection occurs anyway, is $6.45.

Estimating the Effect of Yield Losses on Soybean Prices

In order to determine how soybean prices might respond to yield shocks, we use yearly (1950-2004) yield and price data published by the National Agricultural Statistics Service (NASS). Our first step was to aggregate, using production-weighted averages, the State-level data from NASS to the regional level presented in this report. Next, in order to abstract from yearly variations in output while still accounting for productivity increases over time, we fitted a smooth trend curve for yields in all nine soybean production regions.[7] Example results for the Corn Belt and Southeast can be seen in appendix figure 5, with the open dots representing actual observations and solid lines forming the trend curves.

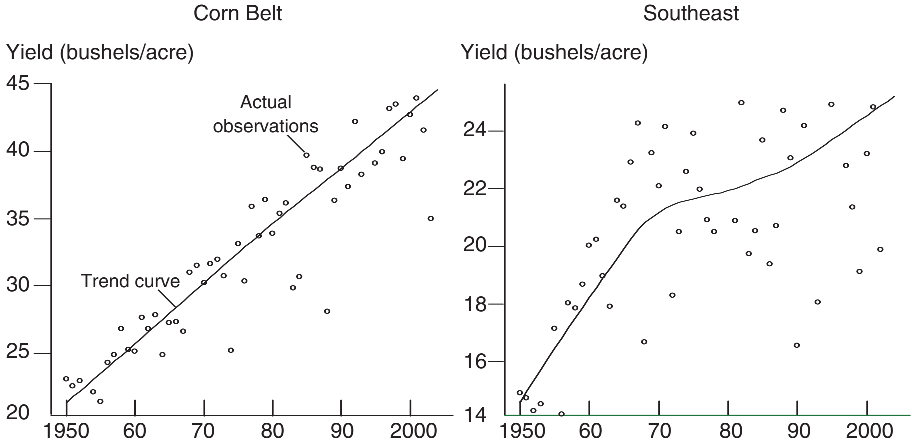
This fitting process allows us to calculate, for each region in each year, a percentage residual yield (i.e., the difference between actual yield and yield predicted by the trend, divided by the yield predicted by the trend).

Having isolated deviations from the trend for yields, we turn to estimating variations in regional soybean prices. We approximate the percentage change in the latter by calculating the year-to-year difference in the natural logarithm of the price, deflated to 1983 dollars. By regressing this value on the percentage residual yield,[8] we obtained an estimate of the percentage change in price that would result from a percentage deviation from the yield trend.[9]

Note that, while these estimates provide some insight into how regional soybean prices and yields have been correlated historically, there is no

Appendix figure 5

Yield trends and shocks in the Corn Belt and Southeast, 1950-2004



[7]Trend curves were created with the "lowess" function in the program R, version 2.1.1.

[8]Only the 20 most recent observations (1984-2004) were included in this regression.

[9]Percentage change in price from year to year will depend not only on this year's yield shocks but also on yield shocks that may have affected the previous year's price. However, including previous year yield residuals as an explanatory regression variable did not lead to significant changes in estimates of the coefficients on current-year price-shock effects.

guarantee that soybean rust will exhibit similar effects as the weather and other production shocks of the past two decades. Especially note the spatial nature of the impacts. If, for example, soybean rust were to spread over the entire soybean-producing part of North America (but drought tends to affect only a few regions at a time), a rust-induced regional price increase would likely be greater than the increase resulting from yield loss caused by drought. Other patterns could cause the reverse to be true.

Consumer Versus Producer Welfare

We calculate the value of information by comparing expected profits with information to expected profits without information. When we account for price-feedback effects, small changes in expected yield lead to small changes in expected price (i.e., the futures price). Thus, if information causes a small increase in expected yield, expected prices tend to decline. If the expected price decline is large enough, farmers' expected profits may decline as a result of the information, even though individual farmers find the information valuable (because, individually, farmers take prices as given). For soybean consumers, however, this price decline is a gain—it simply represents a transfer from producers to consumers. Of course, the opposite is true if the information causes a small decline in expected yield: Prices increase, producers gain more, and consumers lose as a result of the information.

Estimating Average Information Values for Farms with Heterogeneous Prior Beliefs

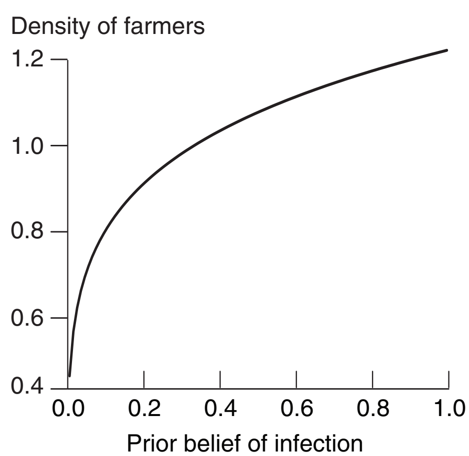
We estimate the average value of information for farmers with heterogeneous prior beliefs of an SBR infection by assuming that these beliefs are distributed according to a beta distribution (see http://mathworld.wolfram.com/BetaDistribution.html). For each region, the beta parameter of the distribution is assumed to equal 1 and the alpha parameter is set so that the average value equals the prior belief in the base case. This distribution assumption implies that farmers' beliefs within each region are widely varying.

The assumed distribution for the Corn Belt is plotted in appendix figure 6. The height of the density curve (labeled "Density of farmers") shows the relative proportion of farmers in the region assumed to have the prior belief of infection plotted along the horizontal axis.

We estimate average information values for each region and information quality by taking 1,000 random draws from the assumed beta distribution, plugging in each draw as the value for P, calculating the associated information values from each draw, and then taking the average of the values resulting from the 1,000 draws.

Appendix figure 6

Assumed density function for farmers' beliefs in the Corn Belt



Appendix table 1

Information values for a representative Corn Belt farm

(a) Prior belief of infection	(b) No information decision	(c) EV, with no information	(d) Quality of information on a scale from 0 to 1	(e) Post-information ("high-risk") probability of infection β	(f) Post-information ("low-risk") probability of infection γ	(g) High-risk decision	(h) Low-risk decision	(i) EV, with information	(j) Value of information per farm	(j) Value of information per acre
		Dollars							------------*Dollars*------------	
0.10	N	106,976	0.2	0.280	0.080	M	N	107,223	248	0.33
.10	N	106,976	.5	.550	.050	M	N	107,942	967	1.30
.10	N	106,976	.8	.820	.020	P	N	109,105	2,130	2.87
.20	M	102,201	.2	.360	.160	M	N	102,776	575	.77
.20	M	102,201	.5	.600	.100	M	N	104,054	1,853	2.50
.20	M	102,201	.8	.840	.040	P	N	106,310	4,110	5.54
.30	M	99,742	.2	.440	.240	M	M	99,742	0	0
.30	M	99,742	.5	.650	.150	P	N	100,615	873	1.18
.30	M	99,742	.8	.860	.060	P	N	103,712	3,970	5.35
.40	M	97,284	.2	.520	.320	M	M	97,284	0	0
.40	M	97,284	.5	.700	.200	P	M	97,979	695	.94
.40	M	97,284	.8	.880	.080	P	N	101,311	4,027	5.43
.50	M	94,825	.2	.600	.400	M	M	94,825	0	0
.50	M	94,825	.5	.750	.250	P	M	96,257	1,432	1.93
.50	M	94,825	.8	.900	.100	P	N	99,106	4,281	5.77
.60	M	92,366	.2	.680	.480	P	M	93,139	772	1.04
.60	M	92,366	.5	.800	.300	P	M	94,761	2,395	3.23
.60	M	92,366	.8	.920	.120	P	N	97,098	4,731	6.38
.70	P	91,646	.2	.760	.560	P	M	92,071	425	.57
.70	P	91,646	.5	.850	.350	P	M	93,491	1,845	2.49
.70	P	91,646	.8	.940	.140	P	N	95,286	3,640	4.91
.80	P	91,441	.2	.840	.640	P	P	91,441	0	0
.80	P	91,441	.5	.900	.400	P	M	92,445	1,005	1.35
.80	P	91,441	.8	.960	.160	P	N	93,671	2,230	3.01
.90	P	91,236	.2	.920	.720	P	P	91,236	0	0
.90	P	91,236	.5	.950	.450	P	M	91,625	390	.53
.90	P	91,236	.8	.980	.180	P	N	92,253	1,017	1.37

Notes: In decision columns (b), (g), and (h), M is monitor/cure, P is prevent, and N is do nothing. In (c) and (j), EV is expected value.

Appendix table 2

Information values for representative farms in all regions

Region	(a) Prior belief of infection	(b) No information decision	(c) Expected yield without SBR	(d) Quality of information on a scale from 0 to 1	(e) High-risk decision	(f) High-risk EV	(g) Low-risk decision	(h) Low-risk EV	(i) EV with information	(j) Value of information per farm	(j) Value of information per acre
			Acres				*Dollars*	------------------------*Dollars*			------------------------
Appalachia	0.67	M	35.80	0.2	P	77,530	M	83,015	79,358	714	0.64
	.67	M	35.80	.5	P	77,282	M	89,572	81,379	2,734	2.45
	.67	M	35.80	.8	P	77,034	N	99,743	84,604	5,959	5.33
Corn Belt	.55	M	44.60	.2	P	91,776	M	96,390	93,873	166	.22
	.55	M	44.60	.5	P	91,497	M	100,413	95,549	1,842	2.48
	.55	M	44.60	.8	P	91,217	N	106,510	98,169	4,461	6.01
Delta	.55	M	31.80	.2	M	93,057	M	103,850	97,963	0	0
	.55	M	31.80	.5	P	87,415	N	114,271	99,623	1,659	.85
	.55	M	31.80	.8	P	86,890	N	130,022	106,496	8,533	4.36
Lake States	.49	M	41.50	.2	M	56,831	M	60,227	58,573	0	0
	.49	M	41.50	.5	P	55,720	M	62,708	59,304	731	1.37
	.49	M	41.50	.8	P	55,509	N	67,085	61,446	2,873	5.38
Northeast	.62	M	38.70	.2	P	41,276	M	43,889	42,281	172	.36
	.62	M	38.70	.5	P	41,145	M	46,559	43,228	1,119	2.37
	.62	M	38.70	.8	P	41,015	N	50,697	44,739	2,630	5.56
Northern Plains	.43	M	36.30	.2	M	67,717	M	72,916	70,688	0	0
	.43	M	36.30	.5	P	63,767	N	77,141	71,409	721	.82
	.43	M	36.30	.8	P	63,428	N	83,496	74,895	4,207	4.78
Southeast	.76	M	25.20	.2	M	1,887	M	4,078	2,408	0	0
	.76	M	25.20	.5	P	1,765	N	7,146	3,046	638	1.44
	.76	M	25.20	.8	P	1,715	N	11,095	3,949	1,540	3.48
Southern Plains	.51	M	26.00	.2	M	21,244	N	29,647	25,343	371	.24
	.51	M	26.00	.5	M	15,652	N	39,069	27,075	2,102	1.38
	.51	M	26.00	.8	P	13,499	N	48,491	30,568	5,596	3.67
Other	.53	M	33.90	.2	M	66,216	M	72,469	69,159	0	0
	.53	M	33.90	.5	P	63,194	N	77,837	70,085	926	.84
	.53	M	33.90	.8	P	62,869	N	86,977	74,214	5,056	4.61

Notes: In decision columns (b), (e), and (g), M is monitor/cure, P is prevent, and N is do nothing. In (f), (h) and (j), EV is expected value. Zero values of information are due to rounding of discrete data.

Appendix table 3

Information values with risk aversion

Region	Prior belief of infection	Base wealth	No information decision	EU, no information	CE of EU, no information	Quality of information on a scale from 0 to 1	High-risk decision	Low-risk decision	CE of EU with information	Value of information per farm	Value of information per acre
		Dollars			*Dollars*				---------------*Dollars*---------------		
Appalachia	0.67	1,649,807	M	1.354	78,371	0.2	P	M	79,248	877	0.78
	.67	1,649,807	M	1.354	78,371	.5	P	M	81,249	2,878	2.57
	.67	1,649,807	M	1.354	78,371	.8	P	N	83,259	4,888	4.37
Corn Belt	.55	1,348,667	M	.889	93,500	.2	P	M	93,772	272	.37
	.55	1,348,667	M	.889	93,500	.5	P	M	95,446	1,946	2.62
	.55	1,348,667	M	.889	93,500	.8	P	N	97,129	3,629	4.89
Delta	.55	918,870	M	(1.184)	96,556	.2	M	M	96,556	0	0
	.55	918,870	M	(1.184)	96,556	.5	P	M	98,085	1,529	.78
	.55	918,870	M	(1.184)	96,556	.8	P	N	101,801	5,245	2.68
Lake States	.49	1,430,615	M	.990	58,476	.2	M	M	58,476	0	0
	.49	1,430,615	M	.990	58,476	.5	P	M	59,251	775	1.45
	.49	1,430,615	M	.990	58,476	.8	P	N	60,424	1,948	3.65
Northeast	.62	1,030,815	M	(.700)	42,017	.2	P	M	42,241	223	.47
	.62	1,030,815	M	(.700)	42,017	.5	P	M	43,183	1,166	2.46
	.62	1,030,815	M	(.700)	42,017	.8	P	N	44,128	2,111	4.46
Northern Plains	.43	1,389,427	M	.929	70,461	.2	M	M	70,461	0	0
	.43	1,389,427	M	.929	70,461	.5	P	N	70,763	302	.34
	.43	1,389,427	M	.929	70,461	.8	P	N	72,540	2,079	2.36
Southeast	.76	1,300,438	M	.493	2,375	.2	M	M	2,375	0	0
	.76	1,300,438	M	.493	2,375	.5	P	N	2,895	520	1.17
	.76	1,300,438	M	.493	2,375	.8	P	N	3,450	1,074	2.43
Southern Plains	.51	1,572,391	M	1.181	24,516	.2	M	N	24,516	0	0
	.51	1,572,391	M	1.181	24,516	.5	M	N	24,516	0	0
	.51	1,572,391	M	1.181	24,516	.8	P	N	26,423	1,907	1.25
Other	.53	915,964	M	(1.492)	68,666	.2	M	M	68,666	0	0
	.53	915,964	M	(1.492)	68,666	.5	P	M	69,613	947	.86
	.53	915,964	M	(1.492)	68,666	.8	P	N	71,780	3,114	2.84

Numbers in parentheses are negative values.

Notes: In the decision columns, M is monitor/cure, P is prevent, and N is do nothing. In other column headings, EU is expected utility and CE is certainty equivalence, which is an expected value calculated under uncertainty.

Appendix table 4

Information values with price effects

Region	Prior belief of infection	No information decision	EV, no information	Quality of information	High-risk decision	Low-risk decision	Low-risk EV	EV, with information	Value of information per farm	Value of information per acre
			Dollars				----------	----------	*Dollars*	----------
Appalachia	0.67	M	78,519	.2	P	M	84,533	79,442	923	0.83
	.67	M	78,519	.5	P	M	90,070	81,174	2,655	2.37
	.67	M	78,519	.8	P	N	100,507	84,540	6,021	5.39
Corn Belt	.55	M	93,302	.2	P	M	99,471	93,819	517	.70
	.55	M	93,302	.5	P	M	101,722	95,424	2,121	2.86
	.55	M	93,302	.8	P	N	107,547	97,568	4,265	5.75
Delta	.55	M	98,203	.2	M	M	104,540	98,203	0	0
	.55	M	98,203	.5	P	N	112,914	99,763	1,560	.80
	.55	M	98,203	.8	P	N	129,996	106,859	8,657	4.43
Lake States	.49	M	58,608	.2	M	M	59,945	58,608	0	0
	.49	M	58,608	.5	P	M	62,826	59,217	610	1.14
	.49	M	58,608	.8	P	N	67,108	61,239	2,632	4.93
Northeast	.62	M	41,936	.2	P	M	45,307	42,216	279	.59
	.62	M	41,936	.5	P	M	47,192	43,152	1,216	2.57
	.62	M	41,936	.8	P	N	51,267	44,481	2,545	5.38
Northern	.43	M	70,621	.2	M	M	72,032	70,621	0	0
Plains	.43	M	70,621	.5	P	M/N	77,804	70,588	(33)	(.04)
	.43	M	70,621	.8	P	N	83,612	74,551	3,930	4.47
Southeast	.76	M	2,419	.2	M	M	3,997	2,419	0	0
	.76	M	2,419	.5	P	N	7,570	3,037	618	1.39
	.76	M	2,419	.8	P	N	11,239	3,962	1,543	3.48
Southern	.51	M	24,807	.2	M	M/N	30,006	24,703	(103)	(.07)
Plains	.51	M	24,807	.5	M	N	38,578	26,605	1,798	1.18
	.51	M	24,807	.8	P	N	48,787	30,456	5,649	3.71
Other	.53	M	69,085	.2	M	M	72,481	69,267	0	0
	.53	M	69,085	.5	P	N	78,162	70,097	830	.76
	.53	M	69,085	.8	P	N	86,884	74,039	4,772	4.35

Numbers in parentheses are negative values.

Notes: In the decision columns, M is monitor/cure, P is prevent, and N is do nothing. In other column headings, EV is expected value.

Appendix table 5

Information values with heterogeneous prior beliefs of an infection

Region	Average prior belief of infection	"alpha" parameter for Beta prior	"beta" parameter for Beta prior	No information decision	EV, no information	Quality of information on a scale from 0 to 1	Average value of information per farm	Average value of information per acre
					Dollars		----------*Dollars*----------	
Appalachia	0.67	2.00	1.00	M	78,644	0.2	239	0.21
	.67	2.00	1.00	M	78,644	.5	1,465	1.31
	.67	2.00	1.00	M	78,644	.8	3,957	3.54
Corn Belt	.55	1.20	1.00	M	93,707	.2	182	.25
	.55	1.20	1.00	M	93,707	.5	1,132	1.53
	.55	1.20	1.00	M	93,707	.8	3,001	4.04
Delta	.55	1.20	1.00	M	97,963	.2	391	.20
	.55	1.20	1.00	M	97,963	.5	2,360	1.21
	.55	1.20	1.00	M	97,963	.8	6,504	3.33
Lake States	.49	.95	1.00	M	58,573	.2	137	.26
	.49	.95	1.00	M	58,573	.5	801	1.50
	.49	.95	1.00	M	58,573	.8	2,185	4.09
Northeast	.62	1.60	1.00	M	42,109	.2	107	.23
	.62	1.60	1.00	M	42,109	.5	660	1.39
	.62	1.60	1.00	M	42,109	.8	1,793	3.79
Northern Plains	.43	.75	1.00	M	70,688	.2	179	.20
	.43	.75	1.00	M	70,688	.5	1,077	1.22
	.43	.75	1.00	M	70,688	.8	3,009	3.42
Southeast	.76	3.20	1.00	M	2,408	.2	81	.18
	.76	3.20	1.00	M	2,408	.5	450	1.01
	.76	3.20	1.00	M	2,408	.8	1,111	2.51
Southern Plains	.51	1.05	1.00	M	24,973	.2	243	.16
	.51	1.05	1.00	M	24,973	.5	1,465	.96
	.51	1.05	1.00	M	24,973	.8	3,734	2.45
Other	.53	1.13	1.00	M	69,159	.2	234	.21
	.53	1.13	1.00	M	69,159	.5	1,396	1.27
	.53	1.13	1.00	M	69,159	.8	3,846	3.51

Notes: In the decision column, M is monitor/cure. In other column headings, EV is expected value and "alpha" and "beta" parameters are defined in the appendix.

Appendix table 6

Summary statistics used for representative farms

Region	Soybean acreage	Net household worth
	Acres	*Dollars*
Appalachia	1,118	1,649,807
Corn Belt	742	1,348,667
Delta	1,956	918,870
Lake States	534	1,430,615
Northeast	473	1,030,815
Northern Plains	880	1,389,427
Southeast	443	1,300,438
Southern Plains	1,524	1,572,391
Other	1,097	915,964

Appendix table 7

Protectant and curative fungicide yield impacts relative to stimates of rust-free yields[1]

Rust-free yield estimate	Efficacy trial yield	Protectant yield impact	Treatments	Curative yield impact	Treatments	Source
Acres	*Acres*	*Percent*	*Number*	*Percent*	*Number*	
2.223	1.914			-14	2	2
2.223	1.765			-21	2	2
2.223	1.776			-20	2	2
2.549	2.149			-16	2	3
2.549	2.190			-14	2	3
2.549	2.090			-18	2	3
2.549	1.832			-28	2	3
2.549	2.767			9	1	4
2.549	2.946			16	1	4
2.549	2.548	0	1			4
2.549	2.712	6	1			4
2.549	2.926			15	1	5
3.359	3.969	18	1			6
3.359	3.641	8	1			6
3.359	3.813	14	1			6
3.359	3.531			5	1	6
3.359	3.656			9	1	6
3.359	3.313	-1	1			6
3.359	3.375	0	1			6
3.359	2.938	-13	1			6
3.359	2.984	-11	1			6
3.359	2.703			-20	1	6
3.359	3.313			-1	1	6
3.359	3.250	-3	1			6
3.359	3.328	-1	1			6
3.359	2.984			-11	1	6
3.359	3.203			-5	1	6
2.750	2.469	-10	1			7
2.750	2.516	-9	1			7
2.750	2.406	-13	1			7
2.750	2.578			-6	1	7
2.750	2.625			-5	1	7
2.686	2.568	-0.97	1.00	-6.95	1.39	Mean

Blank fields indicate no data: Each study considers efficacy of either protectant or curative fungicide treatments.

[1]Soybean yield is reported in metric tons per hectare.

[2]Bayer (2003a) (Trials 1 and 2). The lower bound of the rust-free yield estimate for Mato Grasso do Sul [2.678 (±0.455)] during 2001-02 is used.

[3]Bayer (2003b) (Trial 14). The estimate for rust-free yield in Minas Gerais [2.549 (±0.488)] during 2002-03 is used.

[4]Bayer (2003b) (Trial 15). The estimate for rust-free yield in Minas Gerais [2.549 (±0.488)] during 2002-03 is used.

[5]Bayer (2003b) (Trial 16). The estimate for rust-free yield in Minas Gerais [2.549 (±0.488)] during 2002-03 is used.

[6]BASF (2003) (Jesus, Paraguay). The upper bound of the rust-free yield estimate for Parana [2.862 (±0.497)] during 2002-03 is used.

[7]BASF (2003) (Pirapo, Paraguay). The estimate for rust-free yield in Mato Grasso do Sul [2.750 (±0.476)] during 2002-03 is used.