Journal of Agricultural and Resource Economics 33(3):311–331

Spatio-temporal Risk and Severity Analysis of Soybean Rust in the United States

Anton Bekkerman, Barry K. Goodwin, and Nicholas E. Piggott

Soybean rust is a highly mobile infectious disease and can be transmitted across short and long distances. Soybean rust is estimated to cause yield losses that can range between 1%–25%. An analysis of spatio-temporal infection risks within the United States is performed through the use of a unique data set. Observations from over 35,000 field-level inspections between 2005 and 2007 are used to conduct a county-level analysis. Statistical inferences are derived by employing zero-inflated Poisson and negative binomial models. In addition, the model is adjusted to account for potential endogeneity between inspections and soybean rust finds. Past soybean rust finds and inspections in the county and in the surrounding counties, weather and overwintering conditions, and plant maturity groups and planting dates are all found to be significant factors determining soybean rust. These results are then used to accordingly price annual insurance contracts or indemnification programs that cover soybean rust damages.

Key words: insurance contracts, risk analysis, soybean rust, zero-inflated model

Introduction

The U.S. soybean sector has avoided an onset of soybean rust (SBR) for over a century, while other major world producers have endured considerable yield losses, ranging between 10% and 90%, due to this highly infectious disease (Akinsanmi and Ladipo, 2001; Caldwell and Laing, 2001; Bromfeld, Bonde, and Melching, 1976; Chen, 1989). In the United States, Roberts et al. (2006) report that, if untreated, soybean rust can cause up to a 25% loss of soybean yields. As a leading producer and exporter of soybeans, a disease as potentially devastating as soybean rust can have significant impacts on agricultural economies nationally and abroad.[1] Livingston et al. (2004) estimated that the expected net losses in the United States due to soybean rust can range from $630 million to $1.3 billion, and during the 2006 National Soybean Rust Symposium [American Phytopathological Society (APS), 2006] it was suggested that a typical 800–1,000 acre soybean farm, if infected, will experience a $20,000–$30,000 loss. Yet, under current market conditions in which prices of soybeans have more than doubled over the past year, the economic impacts of soybean rust can be even more dire.

Anton Bekkerman is a Ph.D. candidate, Barry K. Goodwin is William Neal Reynolds Professor, and Nicholas E. Piggott is an associate professor, all in the Department of Agricultural and Resource Economics, North Carolina State University. This work was supported by USDA/ERS Resource Economics Division Cooperative Agreement No. 58-7000-6-0071 entitled "A Feasibility Analysis of Indemnification Plans for the Management of Soybean Rust," and the North Carolina Agricultural Research Service. The authors gratefully acknowledge the helpful comments of the anonymous reviewers.
Review coordinated by Douglas M. Larson.

[1] The United States produced an average of 2.945 billion bushels and exported an average of 40% of the world's soybeans between 2005 and 2007.

In 2007–08, over 63.6 million acres of soybeans were planted in the United States, representing an 11.9 million acre decline from the previous season. This significant decrease in soybean acreage, in combination with a slight reduction in 2007–08 yields, has led to a 13% decline in the supply of soybeans. Despite the lower supply and substantially higher prices, the demand for and total use of soybeans remained relatively constant, resulting in an almost 70% decline in the 2007–08 ending stocks of soybeans. Additionally, during January and February of 2008, the new crop soybean futures used in pricing revenue products [reported by the U.S. Department of Agriculture/Risk Management Agency (USDA/RMA)] steadily rose from $11/bushel to $14/bushel, which implies an average value of $600/acre for 2008–09 soybeans (based on an average of 43 bushels/acre). Ultimately, the tightening of soybean stocks, higher new crop prices, and concerns that a significant increase of soybean rust infections in 2007–08 might affect soybean yields in 2008–09, have led to a heated bidding war for 2008–09 acreage between the corn and soybean markets.

Soybean rust (*Phakopsora pachyrhizi*) is a fungal disease belonging to the "obligately biotrophic" family, which can spread rapidly across long and short distances (Brown and Hovmeller, 2002). The disease is dependent on living tissue and causes tan lesions on a plant's leaf (Sinclair and Hartman, 1995). The fungus causes early defoliation and reduced leaf chlorophyll (Pretorius, 2001; Dufresne and Bean, 1987), leading to fewer soybean plants per acre, fewer pods per plant, smaller pods, and fewer seeds per pod—all of which imply lower yields (Dunphy, 2007). In the United States, soybean rust was first detected in Florida in 2004, prompting an inspection and tracking program by the USDA's Animal and Plant Health Inspection Service (APHIS). In the following years, incidents of soybean rust infections have been frequently reported further west and northwest—regions of major U.S. soybean production. Because soybean rust has over 34 natural hosts,[2] including common weeds such as kudzu (Sinclair, Hartman, and Rupe, 1999), and because winter climatological conditions in the southeastern United States are favorable for soybean rust survival (Livingston et al., 2004; Sinclair and Hartman, 1995), the disease appears to be a long-term concern for U.S. farmers.

The frequency and quantity of rainfall is a primary factor affecting infection rates (APS, 2006), since it is not only a catalyst for disease transport, but also an important aspect of SBR germination. Fungal spores from lesions on infected plants are transmitted by wind and rain to other locations, while germination of the disease is almost entirely dependent on the wetness of the leaf and the air temperature. Infection can occur with only three to six hours of leaf wetness (i.e., typical morning dew) (APS, 2006), and symptoms of rust can be observed between 3–7 days after infection [USDA/Agricultural Research Service (ARS), 1976]. Survival of soybean rust from one season to the next is highly dependent on the life of the host plant.[3] The southeastern United States, which often has year-round above-freezing temperatures, high moisture levels, and a prevalence of kudzu, presents optimal conditions for soybean rust to remain an annual, long-term concern for soybean growers.

In addition to climatological aspects, there are other important factors that affect the probability of soybean rust infection. Yang and Batchelor (1997) found that relative humidity and temperatures have large impacts on determining the spread of the disease.

---

[2] Soybean rust has been found to germinate in an additional 61 experimental hosts (Sinclair, Hartman, and Rupe, 1999).

[3] There is evidence that soybean rust spores can remain in a dormant state for up to six months if temperatures do not fall below freezing (Saksirirat and Hoppe, 1991).

Table 1. Loss Scenarios for U.S. Farmers Under Fungicide Application (2008–09)

Fungicide (cost) [a]	Yield Loss	(Loss + Cost) [b]	Total Loss [c]
Preventive ($32.44/acre)	1%	$38.04/acre	$30,432
Curative ($22.49/acre)	7%	$64.63/acre	$51,704
No Application ($0/acre)	25%	$150.50/acre	$120,400

[a] Fungicide costs were provided by Coastal Agribusiness (2008).
[b] (Revenue Loss + Fungicide Cost); assumes an average of 43 bushels per acre and $14 per bushel.
[c] Assumes an average farm of 800 acres.

As noted by Roberts et al. (2006), planting dates of soybeans have a significant effect on rust probabilities. Moreover, Tschanz and Tsai (1982) found the physiological age of a soybean plant is important in SBR development. These factors imply that the choice of a soybean maturity group as well as a grower's decisions about soybean planting dates might be crucial in accurately modeling infection risks. Treatment and prevention of soybean rust are currently limited to the application of fungicide [see Livingston et al. (2004) for an overview of observed yield losses in Brazil and Paraguay under various fungicide application scenarios]. Roberts et al. (2006) considered several types of fungicide applications to predict potential soybean rust effects in the United States. Table 1 reports potential losses for a U.S. farmer in 2008–09, based on the analyses discussed by Roberts et al.

Due to the quickly spreading and highly infectious nature of this disease, there exists a significant risk of infection and yield loss. With current market demand for corn crowding out soybean acreage and decreasing soybean supply, accurate knowledge of the determinants of infection risk might prevent an exacerbation of reduced soybean production and stocks.

Using the infection tracking program enacted by the USDA, we model the underlying risks of soybean rust infection in the United States by combining extensive farm-level information with detailed data about climatological and biological factors. Based on more than 32,000 inspections over the 2005–2007 period, we estimate and compare several empirical specifications for measuring infection risks. Factors that contribute to the spatial and temporal spread of risks are considered. The results of these models are then used to identify factors that affect infection risks, calculate potential yield losses, and determine actuarially-fair premium rates for single-peril insurance policies. These specific-peril insurance plans can be used as additional or alternative methods of protection for soybean growers to indemnify soybean rust infections. The following sections present a modeling framework, empirical specifications and results, and estimates of premium rates for annual insurance contracts.

The Model

In developing an insurance contract for addressing a particular hazard such as a disease and the likelihood of infection, one design strategy is to quantify the risk of the specific peril. Current insurance programs that provide relief in case of yield loss due to soybean rust are a part of all-risk inclusive plans, which may not reflect the actuarially-fair premium rates for specific hazards. Existing yield, price, and revenue plans of insurance often cannot appropriately measure all of the risks the insurance policy intends to cover.

In some cases, there are hazards for risks which can be specifically identified and quantified. For such a hazard, it is possible to derive actuarially-fair insurance rates based only on the factors and risks applicable to the hazard. For example, the risks of a flood or fire can be measured and used to calculate precise insurance rates. In addition, measuring and quantifying these risks is often easier than designing an insurance contract that attempts to examine the interdependence of risks from all possible hazards. Similarly, it is appropriate to analyze the risks that are specific to soybean rust, which could be used for a specific-peril insurance contract for soybean rust designed to minimize the shortcomings associated with all-risk contracts.

A central objective of any viable insurance plan is to maintain a loss ratio that is at or below unity. The loss ratio measures the proportion of total indemnities paid out relative to the total premiums collected. In order to preserve a relative equality between indemnities and premiums, it is necessary to identify the actuarially-fair insurance premium rate—the rate at which the loss ratio would be unity. For a soybean farmer, an actuarially-fair premium rate is the ratio of the expected yearly payment for soybean rust insurance to the total liability the farmer could incur due to the disease under the terms of the insurance plan. In the case of an analogous indemnification policy, an actuarially-fair premium rate would be calculated by setting the expected payouts equal to payments into the indemnification fund.

To be actuarially sound, an insurance plan must determine and model the risks associated with a particular hazard in order to ensure the premium rate is neither too high nor too low. If the premium rate is set too high, then less risky farmers will not purchase the insurance, potentially leaving a smaller, more risky pool of insurance-purchasing farmers. Conversely, premium rates set too low result in indemnity payouts that are offset by the premium payments, leading the program to be insolvent. Deriving an actuarially-fair rate involves modeling risks using a conditional probability density function that describes the outcomes if a hazardous event occurs.

Suppose farmer i purchases an insurance policy that guarantees some proportion of the expected yield, $\theta E[y]$, where $0 < \theta \leq 1$. If, in year t, soybean rust reduces yields below the guaranteed amount, then the farmer will receive a compensatory payment up to the yield guarantee. Denoting the expected yield with μ, the indemnity payment is computed as:

$$(1) \qquad Indemnity_{i,t} = Price_t * \max\{0, \theta\mu - y_{i,t}\},$$

where $Price_t$ is a predetermined amount per unit of loss that is paid in case of a loss. To calculate the actuarially-fair premium rates, it is necessary to calculate the expected losses a farmer in location i might incur. Normalizing the prices paid for a loss to one, expected losses can be expressed as the product of the probability of a loss and the expected loss, conditional on actual yields being below the expected yields. This is expressed as:

$$(2) \qquad E[Loss]_{i,t} = \Pr[y_{i,t} < \theta\mu] * \left(\theta\mu - E[y_{i,t} \mid y_{i,t} < \theta\mu]\right).$$

In some insurance programs, the loss occurs as a function of some binary event with no provisions for partial payouts. For example, a life insurance payment is made only if there is a death, and no other provisions result in partial payouts. This structure can also be made applicable to the cases of soybean rust, where an infection corresponds to a loss that is compensated at a predetermined payment level, thus simplifying the calculation of actuarially-fair premium rates for an insurance policy. In this case, the actuarially-fair premium, which is set equal to the expected loss, is determined directly by the probability of a loss occurring. This is given by:

$$Rate = E\,[Loss]_{i,t} = \Pr\,[Loss]_{i,t} * \bar{P}. \tag{3}$$

The total payment, $\bar{P}$, is fixed in the amount that would cover the cost of a curative fungicide treatment and a fixed percentage of yield loss. The subsidization of curative fungicide through the indemnification policy can provide dual benefits. First, because many of the curative fungicides can also be used for the purpose of protection against future infection, their application can provide valuable assistance in curing the current soybean rust outbreak, as well as preventing future spread. Second, the treatment and prevention of additional infections will help suppress the transfer of soybean rust to nearby farms. In this manner, the subsidization of curative fungicide might be viewed as providing a positive externality.

In this type of insurance policy, accurately modeling the probability of a loss event is crucial in the determination of actuarially-fair premiums. In modeling the probability of a loss, it is important to recognize the multitude of factors that might affect this probability. For example, crop decisions and planting dates are important determinants of loss risk for soybean rust. Soybeans double-cropped with wheat are often more susceptible to soybean rust because they are planted later in the season. Since rust is most prevalent during the later summer months, accurate assessments of infection and loss risks must be conditioned on planting decisions. Another factor found to be important in influencing infection risk is the soybean maturity group. Insurance contracts that identify deterministic factors may produce more precise and actuarially-fair premium rates.

Another important issue for developing a specific-peril insurance product is the insurance period. Typically, an insurance contract period is either specified for a calendar or crop year, and the terms of the contract, such as the payment per unit of loss, are determined prior to the beginning of the year. Due to this condition, probability models must be based on information available prior to the beginning of the insurance contract period. Any information that becomes known after the start of the contract year must be assumed to be unknown by both the principal and agent, and so cannot be used in devising a contract for that insurance period.

One example of information that is important to risk but which cannot be determined prior to constructing a contract is weather. Infections of soybean rust are significantly affected by different weather characteristics. However, accurately predicting departures from normal weather conditions at distant periods (such as those required in an insurance program) is difficult, if not impossible. For instance, knowledge of heavy rains and high winds in a particular area during the previous year, which caused increased rust infections, cannot be used in modeling infection risks for the current year because these conditions might not repeat in the following year. Nevertheless, if there is knowledge that an area was highly infected in year $t-1$, and that the same area experienced warm temperatures during the winter (which increases the probability of survival of soybean rust), then this information can be used for contracts in year t, since these facts are available prior to the start of the next insurance period. Additionally, long-run weather patterns for a location can be used as measures of expected climatological conditions.

These issues, which are important in devising an insurance contract, must be taken into consideration when modeling the risk of soybean rust infection. Factors used for conditioning the probability of rust must be measurable prior to the beginning of the contract period. With soybean rust, there are a variety of measurable spatio-temporal attributes that affect the likelihood of infection. Because soybean rust spores are highly transferable and infectious, the likelihood of finding soybean rust is significantly influenced by the spatial and temporal juxtaposition of inspected farms. An appropriate risk-modeling technique for successfully capturing these characteristics involves conditioning soybean rust infection at a particular location on the historical infection status in nearby locations. Such a conditional probability of infection is represented by:

$$\Pr[S_{i,t}] = f(S_{i,t} \mid S_{j,t-1}, S_{k,t-1}, \ldots, Z_{i,t}) + \varepsilon_{i,t}, \tag{4}$$

where $S_{i,t}$ corresponds to the number of soybean rust infections in location i during time t, $S_{j,t-1}$ is the number of soybean rust infections in a neighboring location j during time $t-1$, and $Z_{i,t}$ are other factors that increase the probability of soybean infection in period t at location i. In our analysis, neighboring locations are defined as those that are connected by a common border, a major road, a body of water, or if the locations meet at a corner. The random error term is denoted by $\varepsilon_{i,t}$.

As with many insurance policies, there are often concerns about adverse selection and moral hazard. The former refers to the concept that asymmetries in information available to the principal and the agent can lead to a price of an insurance policy that is too low or too high. Moral hazard occurs when an insured agent intentionally contributes to the probability of loss. In general, the principals attempt to enact policies which minimize both adverse selection and moral hazard. For example, to address adverse selection, principals can: (*a*) require that all acreage for a particular farm is insured; (*b*) establish contract dates prior, when critical information (such as weather) becomes available to the farmer; (*c*) provide policies spanning several years in order to prevent the purchase of a single-year policy that might necessitate a large payout; or (*d*) offer area-wide programs. Similarly, efforts to reduce moral hazard include the enactment of "good farming practices" or documentation of required actions, such as receipts for fungicide purchases.

Due to the novelty of soybean rust in the United States, the RMA has only minimally augmented its premium rates to reflect the threat of this new disease. This lag in implementing changes might increase the possibility of both adverse selection and moral hazard. First, the premium rates used in many of RMA's insurance policies are adjusted quite slowly and often depend on a long period of historical data. The programs that have not incorporated the probabilities of infection and loss due to soybean rust may be subject to an increased adverse selection problem. Further, the RMA requires only a brief list of provisions a farmer must follow in order to qualify for coverage in case of damages due to soybean rust. Insured agents must keep informed about soybean rust outbreaks in the vicinity, know the methods for preventing and eradicating the disease, and scout fields and document their findings. Most importantly, the current provisions do not require a farmer to spray preventative fungicide—only curative fungicide in the event of an outbreak—to be eligible for compensation.

In this study, we attempt to address the issue of adverse selection in two ways. First, we calculate the probability of infection directly and compute actuarially-fair premiums based on this probability. This rate should minimize the potential for adverse selection given the focus on this specific peril. Additionally, we assume the contract period begins on the first day of each calendar year, which might preclude farmers from learning climatological conditions during early spring. Knowledge of weather patterns in early spring can affect the probability of a location to be infected with soybean rust. Preventing farmers from knowing these conditions prior to purchasing an insurance policy can assist in averting adverse selection. Monitoring costs and other types of moral hazard might be minimal in a policy for soybean rust protection because a farmer who does not apply fungicide will experience a much greater loss than those who follow the application guidelines—in this manner, cheating is minimized.

Empirical Framework

Data

This study uses farm-level inspection data collected by the USDA, the National Plant Diagnostic Network (NPDN), and the National Agricultural Pest Information System (NAPIS). Inspection data used in our analysis were collected between January 2005 and November 2007. Weather statistics for the same time period were obtained from the North American Regional Reanalysis database, which is maintained by the National Climatic Data Center (NCDC). Statistics about typical planting dates and maturity groups were assembled from various sources, including the USDA's National Agricultural Statistics Service (NASS) and RMA. The data consist of 32,089 reported inspections from 1,097 U.S. counties, located mostly in states along and east of the Great Plains.

The unit of observation in this analysis is the county. Although the data set consists of farm-level inspections, neither the unique identification of farms nor the exact geographical locations were available. However, in the case of soybean rust, a county-level analysis is appropriate in modeling infection risk and developing an insurance contract. This is the case for several reasons. First, unlike other diseases, soybean rust does not differentiate among different soybean cultivars, implying that, under certain climatological conditions (mentioned previously), rust can occur on any farm in the county. Second, because soybean rust is highly contagious and easily transmitted, there is a significant probability for multiple farms in the same county to be infected. Finally, determining insurance premiums at the county level allows the smoothing of premium rates across individual farms, which may be advantageous for insurance providers.

Econometric Specification

In modeling the risk of soybean rust infection, it is necessary to apply the conditional probability described in equation (4) to the available data. Our study considers several approaches to modeling this risk in an effort to determine the best approach. The first approach is a simple probit specification that models the probability of one or more infections in a county during a calendar year. Alternatively, it is possible to use count-data models to measure the number of soybean rust infections in a particular county.

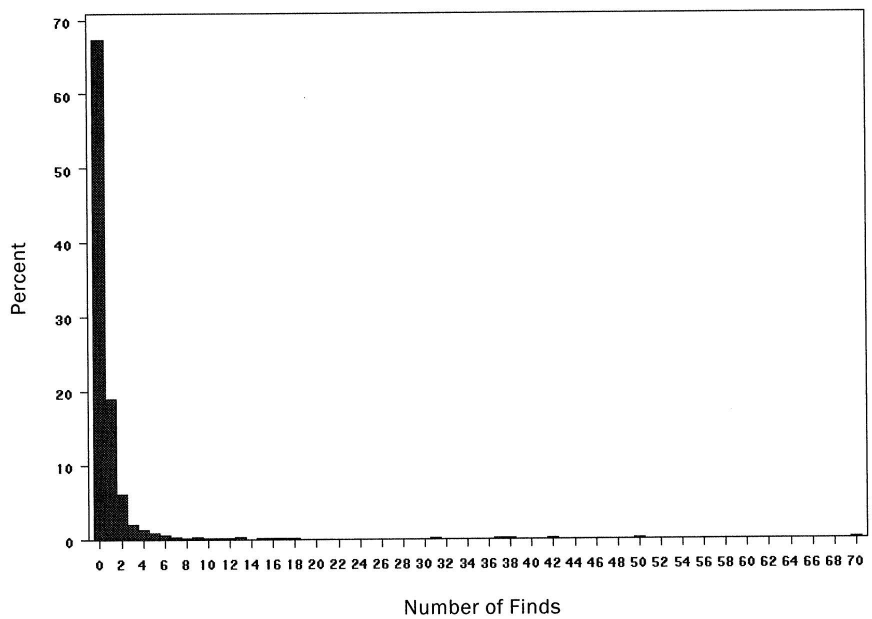


Figure 1. Total soybean rust infections, in percent

We examine both the Poisson and negative binomial processes to investigate the count of rust infections. Modeling rust infections with a negative binomial specification relaxes the Poisson assumption that the mean is equal to the variance. A likelihood-ratio test can be performed to test the null hypothesis that the coefficient of overdispersion is zero in the negative binomial specification.

An important aspect of the data introduces additional empirical challenges with respect to the use of typical Poisson and negative binomial specifications. Although the occurrence of soybean rust infections has been shown to increase significantly over the time period of the data, there is a preponderance of observations for which no rust was found. Illustrated in figure 1, this characteristic of the data might imply that counties with no rust finds come from a data-generating process which is neither Poisson nor negative binomial. Without capturing the different data-generating processes, modeling the entire data set by using a single specification could lead to inaccurate parameter estimates and inappropriate inferences.

Previous research indicates regime switching-type models or mixture models can provide a more accurate representation of the zero and nonzero outcomes (e.g., see Heilbron, 1989; Lambert, 1992; and Johnson, Kotz, and Kemp, 1993). These mixture models first capture the probability of an outcome to be nonzero, and then represent the nonzero outcomes with a count-data model. This type of approach is often referred to as "zero-inflated," because the probability mass at zero is inflated relative to a standard Poisson distribution, and probabilities of the nonzero outcomes are scaled to sum to one. In this study, the probability of at least a single soybean rust infection is modeled using a probit model, and the Poisson and negative binomial specifications are used to model the generating process of the positive rust infections.

The covariates used in estimating the zero-inflated models are listed in table 2. Many of the covariates are chosen to represent the information that has been shown to affect

Table 2. Description of Variables and Summary Statistics

Variable	Number of Observations	Mean	Std. Dev.	Minimum	Maximum	Description
Zero Infections	1,097	14.56517	21.34679	0	386	Inspections with no infections
SBR Research Sites	1,051	9.42531	11.52359	0	97	Experimental plots for early detection
E[Net Farm Income] ($1,000s)	1,095	16.64657	25.44264	−0.43038	237.9526	Expected net farm income
Soy : Other Grains	1,097	0.33083	0.24772	0	1	Ratio of planted soybeans to other grains
Infections	1,097	0.99453	3.89904	0	70	Inspections with an infection
Inspections	1,097	15.54512	10.38719	0	145.5053	IV estimate of inspections
Nearby Infections	1,097	3.25068	8.23348	0	120	Number of infections in nearby counties in previous years
Overwinter Temp / Precip.	1,097	0.50414	0.26908	0.03436	6,022.19	Interaction variable: Precipitation during farm season $(t-1) \times$ overwinter temperature
Overwinter Temp / Humid.	1,097	2,476.9	1,084.38	325.11070	6,520	Interaction variable: Humidity during farm season $(t-1) \times$ overwinter temperature
Overwinter Temp / Wind	1,097	29.89339	32.72126	2.65216	330.0878	Interaction variable: Wind speeds during farm season $(t-1) \times$ overwinter temperature
Soy Harvested : Planted	1,097	0.76172	0.40362	0	1	Ratio of harvested to planted soybeans
Soy Plant Date	1,097	—	—	—	—	Planting date of soybeans (RMA)
Categorical Variables: [a]						
Soy Maturity Group 1	—	—	—	00	2	Maturity group of planted soybeans (northern U.S.)
Soy Maturity Group 2	—	—	—	3	5	Maturity group of planted soybeans (middle U.S.)
Soy Maturity Group 3	—	—	—	6	8	Maturity group of planted soybeans (southern U.S.)

[a] Categorical variables are set equal to 1 if county i plants soybeans of a maturity group in the specified range; otherwise set to 0.

the risks of soybean rust infection. Primarily, this is related to the pathological characteristics of soybean rust. In general, three important categories are addressed with the choice of the covariates: (*a*) the ability for rust to be transferred from one county to another, (*b*) the conditions that allow rust to reappear in the next year, and (*c*) the characteristics of soybean planting practices. For example, the climatological interaction variables are used to explain the patterns of spread of soybean rust, as well as the disease's ability to survive the winter. Attributes such as precipitation, wind speeds, and relative humidity have been shown to significantly affect soybean rust spread. However, additional information about the overwinter temperature, which has been shown to be a primary reason for soybean rust survival over the winter months, can be even more revealing. Specifically, a county that experienced high precipitation and strong winds during the planting season (increasing the probability of soybean rust infection) and then had no freezing temperatures in the winter (increasing the probability of soybean rust survival) would be expected to have an increased chance of developing rust in the next season.

To test for zero inflation, it is inappropriate to simply set the parameters of the probit selection model to zero, because the standard models and the zero-inflated models are nonnested. Rather, we use a nonnested test for competing models, as proposed by Vuong (1989). The test compares the probability that the distribution of one model is closer to the true distribution than the distribution of a competing model. Since the maximum log likelihood of a model can be considered to be a good estimate of the distance between the model and the true distribution, the test is based on the likelihood-ratio statistic. The test statistic ν (the ratio of likelihoods) has a limiting standard normal distribution. For example, for $\alpha = 0.05$, the test supports a particular model if $\nu > 1.96$, the alternative model if $\nu < -1.96$, and neither model if $-1.96 \leq \nu \leq 1.96$.

One issue requiring additional attention is the possibility of dependence between the soybean rust finds and the number of inspections. Because observing a rust infection is wholly dependent on an inspection, it is expected that inspection efforts might be targeted to areas with a larger probability of infection.[4] This is the case in our data set, where 25% of the counties had more soybean rust infections than in the previous year, and, on average, there were more than two additional inspections in the following year within those counties. This finding suggests the probability of infection may be endogenous to the level of protection. This relationship is given by $SBR_t = C_o + \psi m_t + \delta \mathbf{z}_t + \varepsilon_t$, where SBR_t is the number of infections at time t, C_o is an intercept term, m_t is the number of inspections, $\mathbf{z}_t$ is a matrix of other explanatory variables, and $\text{cov}[m_t, \varepsilon_t] \neq 0$.

To address this potential endogeneity, we estimate the model in two stages. In the first stage, inspections are regressed on a set of instrumental variables (IVs) such that $m_t = C_1 + \theta \mathbf{n}_{t-1} + \eta_t$, where $\mathbf{n}_{t-1}$ is a vector of explanatory variables relevant to the number of inspections. Next, using predicted inspections, $\hat{m}_t$, we estimate the second-stage specifications (e.g., Poisson or ZIP) using maximum likelihood. To derive a consistent estimate of the covariance matrix for the parameters of the IV estimation, we employ a bootstrap procedure. Specifically, we randomly sampled with replacements from our data set, and parameters were estimated for each replication. Using 5,000 replications, consistent standard errors were calculated.

[4] Soybean rust infections can exist, but unless an inspection occurs, the infection remains unobserved and unreported.

In some instances, it is possible to estimate a reduced-form equation, which uses the instruments directly to estimate a one-stage specification. Still, this would not allow for a direct interpretation of the structural coefficient of the variable the instruments replace. In this study, however, we are interested in measuring the effect of inspections on the probability of a soybean rust infection. Further, predictions from structural and reduced-form linear models are, in general, equivalent. In the case of highly nonlinear specifications such as the zero-inflated Poisson and zero-inflated negative binomial, predictions might be significantly different. Thus, because the main purpose of the instrumental variables is to address the issue of endogeneity between the inspections and soybean rust occurrences, we implement the structural model.

An additional issue considered is the potential presence of spatial autocorrelation in the estimated residuals. Because we are employing a data set with a spatial dimension, it may be necessary to correct for the spatial autocorrelation that could reflect the effects of omitted, spatially correlated variables. Although there are nonstructural methods to correct for the spatial correlation, we attempt to capture these effects directly by including a variable that measures the number of infections in neighboring counties during the preceding year. To test for the potential significant effects of spatial correlation, we implement the nonoverlapping block bootstrapping procedure proposed by Carlstein (1986). This technique involves randomly selecting an individual observation, and then adding all other points falling within the same time period and spatial block, l. In general, blocks must be chosen whereby the observations within each lth block retain their spatial dependence, but each block's residuals are not autocorrelated with the residuals of any other block. In our model, we choose an lth block to consist of observations falling within the same agricultural statistical district (crop reporting district) of the randomly selected observation.[5]

Empirical Results and Analysis

The results of each specification are used to derive measures of the conditional probability of soybean rust infection in each county. These probabilities can then be applied to determine actuarially-fair insurance policies for losses related to the disease. To model the spatio-temporal dispersion of rust more accurately, several conditioning variables are used within various econometric specifications. These variables are chosen in accord with past research about the pathological attributes of soybean rust and biological characteristics of soybeans (discussed above). Table 2 reports the summary statistics and descriptions of variables used to model infection risks.

Results for Preliminary Models[6]

As discussed above, there is concern of endogeneity between the number of probability of infections and the frequency of inspections. To address this issue, we use instrumental variables to model inspections, and then use the estimates to construct an uncorrelated predicted inspections variable within the specifications modeling rust infections.

[5] Agricultural statistical districts are defined by USDA/NASS.

[6] For brevity, the results for preliminary models are not reported in detail; however, a concise discussion of these results motivates the explanation of the results for the preferred models. These results are available from the authors upon request.

Ordinary least squares is employed to estimate inspections as a function of expected farm income, the proportion of soybeans planted to grains in the previous period, and the number of inspections in the previous year that did not find soybean rust.

Using the results from the IV model, a simple probit model was constructed to estimate infection status within a discrete framework. If a county had one or more infections, then its status variable was set to one; otherwise, it was set to zero. Within the sample of 32,089 inspected farms in 1,097 counties, nearly 33% of the counties had at least one soybean rust infection. The probit model estimates indicate that only the infections in the previous year, the previous year's proportion of soybeans harvested to soybeans planted, and the maturity group of the planted soybeans are significant in explaining infections in the current period. As expected, the probit model reveals that infections in the preceding year are statistically significant in raising the probability of infections in the current period. Also, based on the harvested-to-planted ratio coefficient, a county having more soybean acres (and accordingly more hosts) might be more susceptible to soybean rust infection. These findings are consistent with past epidemiological studies (e.g., see Kim and Shanmugasundaram, 1979). Finally, even though all soybean varieties are susceptible to rust, the maturity group coefficient shows later-maturing soybeans are more likely to be infected. This is due to the fact that maturity groups correspond to the location and climate in which soybeans are grown. Soybeans identified with a higher maturity group are typically grown in the southern United States, where conditions for soybean rust infections are more favorable.

To exploit the discrete counts of infection, the Poisson and negative binomial processes are used as alternative models to the probit specification. As with the probit model results, the historical infection status, ratio of harvested to planted soybean acres, and soybean maturity group significantly increase the probability of soybean rust infections. Additionally, results of the Poisson specification indicate that an increase in the number of inspections and/or nearby infections will increase the probability of soybean rust infection. These relationships are consistent with the spatial and climatological research, which suggests soybean rust can affect locations situated near already infected areas, historically infected areas are more susceptible to future infections, and weather patterns are a significant factor in determining the probability of soybean rust infections.

The results of the negative binomial specification are similar to the Poisson, except for insignificant coefficients on the inspections and nearby infections variables. Both the Poisson and negative binomial models yield similar patterns of infection risk—mostly concentrated in the southeastern United States and the Mississippi Delta. However, the results also confirm a significant probability of infection in the Midwest and Great Plains regions.

Results for Preferred Models

As noted above, the preponderance of observations that have no soybean rust infections might adversely affect the empirical results when fitting the simple Poisson and negative binomial processes to the data. In light of this, we use two "zero-inflation" models, which are variations on the Poisson (ZIP) and negative binomial (ZINB) specifications. The estimation of the zero-inflated models is performed using the maximum-likelihood approach, and the results are shown in table 3 (ZIP) and table 4 (ZINB). These models provide a much richer understanding of the effects of important spatial, temporal, and

Table 3. Two-Stage Bootstrapped Zero-Inflated Poisson (ZIP) Model Results

Probit Selection Model				Zero-Inflated Poisson Model for Positive Infections			
Parameter	Estimate	Std. Error	Elasticity	Parameter	Estimate	Std. Error	Elasticity
Intercept	2.95420***	0.05824		Intercept	3.51100***	0.03207	
Infections, t – 1	0.30880***	0.05530	0.183	*Infections, t* – 1	0.02893***	0.00196	0.022
IV Inspections	–0.00373	0.00286	–0.002	*IV Inspections*	0.02388***	0.00100	0.371
Nearby Infections, t – 1	–0.00316***	0.00095	–0.002	*Nearby Infections, t* – 1	0.01514**	0.00182	0.037
Overwinter Temp / Precip.	–0.02512*	0.01623	–0.012	*Overwinter Temp / Precip.*	0.30810***	0.05312	0.155
Overwinter Temp / Humid.	–0.00016**	0.00002	–5.7E-05	*Overwinter Temp / Humid.*	0.00012***	0.00001	0.277
Overwinter Temp / Wind	–0.00046	0.00142	–0.0002	*Overwinter Temp / Wind*	0.00219**	0.00087	0.065
Soy Harvested : Planted	0.49320***	0.07422	0.318	*Soy Harvested : Planted*	–0.01544	0.04496	–0.012
Soy Plant Date	–0.00009***	3.48E-06	–5.9E-06	*Soy Plant Date*	–0.00041***	1.91E-06	–6.882
Soy Maturity Group 2	–1.87090***	0.11230	–0.538	*Soy Maturity Group 2*	2.41410***	0.11340	0.731
Soy Maturity Group 3	–1.12260***	0.07046	–0.331	*Soy Maturity Group 3*	3.27130***	0.03361	1.560

Akaike Information Criterion (AIC) = 3,006.1
Schwarz Bayesian Criterion (SBC) = 3,116.7

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

Table 4. Two-Stage Bootstrapped Zero-Inflated Negative Binomial (ZINB) Model Results

Probit Selection Model				Zero-Inflated Negative Binomial Model for Positive Infections			
Parameter	Estimate	Std. Error	Elasticity	Parameter	Estimate	Std. Error	Elasticity
Intercept	−1.31840**	0.5608		Intercept	−1.70580	2.55860	
Infections, t − 1	4.63410***	0.6268	2.740	*Infections, t* − 1	0.10610***	0.01799	0.079
IV Inspections	−2.12820***	1.3619	−1.015	*IV Inspections*	0.03569***	0.00313	0.555
Nearby Infections, t − 1	2.43950***	0.2619	1.212	*Nearby Infections, t* − 1	0.01622*	0.00594	0.040
Overwinter Temp / Precip.	−1.34110***	0.5219	−0.664	*Overwinter Temp / Precip.*	0.16790*	0.09977	0.085
Overwinter Temp / Humid.	0.00272***	0.0002	9.69E-04	*Overwinter Temp / Humid.*	−0.00003	0.00002	−0.069
Overwinter Temp / Wind	−0.57980	1.1887	−0.287	*Overwinter Temp / Wind*	0.00366**	0.00173	0.109
Soy Harvested : Planted	6.43110***	0.5951	4.155	*Soy Harvested : Planted*	0.39580***	0.07185	0.301
Soy Plant Date	0.00070**	3.2E-05	4.6E-05	*Soy Plant Date*	−0.00001***	3.47E-06	−0.168
Soy Maturity Group 2	−3.58850***	0.8677	−1.031	*Soy Maturity Group 2*	2.24280	1.83640	0.679
Soy Maturity Group 3	−11.69110***	0.6839	−3.449	*Soy Maturity Group 3*	3.37070**	0.81680	1.607

Akaike Information Criterion (AIC) = 2,225.4
Schwarz Bayesian Criterion (SBC) = 2,340.8

Note: Single, double, and triple asterisks (*) denote statistical significance at the 10%, 5%, and 1% levels, respectively.

biological factors on soybean rust infection probabilities. Additionally, the results of Vuong's nonnested test suggest that in both the Poisson and negative binomial cases, the zero-inflated specifications are preferred.[7]

Generally, the coefficients in the two specifications indicate similar relationships between infection probabilities and the explanatory variables. In the probit selection models for ZIP and ZINB, the direct relationship between the lagged infections variable and the probability of no infection seems to indicate there might be a risk mitigation or preparation effect. A location that has been infected in the previous year may apply preventive measures, which could lead to a decrease in infection probability in the following year. Specifically, a 1% increase in infections during t implies a 0.183% (ZIP) and 2.74% (ZINB) decrease in infection probability at $t + 1$. Additionally, the zero-inflated negative binomial model appropriately describes the effects of climatological factors on SBR infection probabilities. For example, an additional percentage increase in the value of the variable describing the interaction between the precipitation in $t - 1$ and overwintering temperature implies a 0.664% increase in the probability of soybean rust infection. Similarly, infection probability rises if there are higher wind speeds and temperate overwintering temperatures.

The ZINB model (table 4) also shows a significant effect of soybean maturity groups on the infection probability. Maturity groups correspond to the geographical planting location and the time to maturity of a soybean plant. There are 10 total soybean maturity groups [see McWilliams, Bergland, and Endres (1999) for a biological overview of soybean maturity groups], which were sorted into three categorical variables according to geographical regions. In the empirical specification, these groups were modeled as dummy variables. Relative to soybeans found in maturity groups ranging between 00 and 2 (the base group), plants that are between maturity groups 3 and 5 are 3.5885 times more probable to be infected, and those within maturity groups ranging between 6 and 8 are 11.6911 times as susceptible. This is consistent with the pathological behavior of soybean rust. Soybean plants that are in a higher maturity group are planted in a more southern region and take longer to mature, making them increasingly susceptible to SBR infection.

When comparing the two models, it is often useful to examine the information criteria measures such as the Akaike Information Criterion (AIC) and the Schwarz Bayesian Criterion (SBC). These measures show that the ZINB provides a better fit than the ZIP model. For the ZINB model, the predicted probabilities are presented in Figure 2. As do all of the specifications, both of these models indicate high probabilities of infection in the south and southeastern United States. These results confirm outcomes of past studies, which conclude that optimal conditions for soybean rust exist in the southeastern states.

Finally, to consider whether including a variable that describes infection status in nearby counties is sufficient to capture the spatial correlation of infections, we reestimate the models using a nonoverlapping, block bootstrap procedure. In general, the results are quite similar to those estimated without the block bootstrap.[8] One major difference, which was typical in each block bootstrapped model, is the statistical insignificance of the nearby infections coefficient. This finding might imply that directly controlling for

[7] For ZIP vs. Poisson, $\nu = 4.3342$; for ZINB vs. negative binomial, $\nu = 5.0301$.

[8] These results are omitted here, but are available from the authors on request.

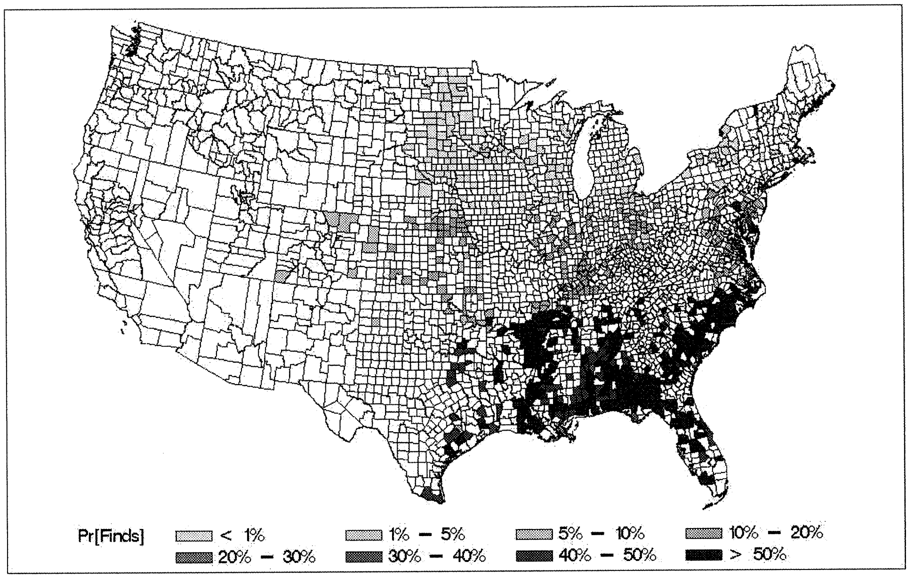


Figure 2. Infection probabilities in U.S. counties: ZINB model predictions

the spatial autocorrelation of residuals, by including a structural component such as the infection status of nearby locations, is appropriate for this model. When an explicit correction for spatial correlation is performed using the nonoverlapping block bootstrap, this particular variable becomes insignificant.[9]

Indemnification Premiums

The primary goal of the preceding analysis was to construct models that can measure the risk of a soybean rust infection, and then use these probabilities to determine actuarially-fair insurance or indemnification premiums. In our analysis, an actuarially-fair premium is determined directly from the expected loss, which is calculated by using the conditional probabilities of soybean rust infection from the above models. The expected loss is expressed as follows:

$$E[Loss]_{i,t} = \Pr[County_{i,t} = Infected \mid X_{i,t}] * Payment, \tag{5}$$

where the infection status in county i at time t is conditioned on covariates $X_{i,t}$. An equivalent representation of equation (5) is given by:

$$E[Loss]_{i,t} = F_{i,t}(X\beta) * Payment, \tag{6}$$

[9] As keenly pointed out by an anonymous referee, the ability of soybean rust to spread rapidly over space might suggest that the spatial dependence of infections may be across a larger geographic area. In an attempt to address this concern, the lth block was expanded to include the agricultural statistical district (ASD) as well as all bordering ASDs. However, the results were not significantly different from performing a block bootstrap using a smaller geographical area. Hence, the convergence of parameter estimate variances was successfully achieved without the need to expand the size of the block.

where $F_{i,t}(\cdot)$ denotes measures of conditional infection risk that are determined by each empirical specification.[10] *Payment*, which represents the indemnity payment per acre for losses due to a soybean rust infection, is assumed to correspond to each of the three loss scenarios described by Roberts et al. (2006). The authors define potential yield losses as a function of fungicide application. If preventive fungicide is applied, then the predicted losses due to soybean rust are estimated to be approximately 1%. Applying curative fungicide would result in a yield loss of approximately 7%. If no fungicide is used, then the authors predict up to a 25% loss. We assume a fixed indemnity is paid to the grower to compensate for the cost of the curative fungicide and the 7% yield loss. In addition, this payment would be made to all insuring growers within the county, regardless of whether or not a grower has reported an infection (since this is a county-level insurance policy), which can be used as a loss mitigation treatment. To determine the expected worth of losses, we use new crop discovery prices estimated by the USDA/RMA (2008). The new crop discovery prices are used for revenue insurance products, which depend on November new crop soybean futures. Thus, for our analysis, *Payment* for county i is expressed as:

$$\text{(7)} \qquad Payment = (InsuredAcres)_{i,t} * \{(Yield_{i,t} * PercentageLoss) * SX_t + FungicideCost\},$$

where $InsuredAcres_{i,t}$ corresponds to the insured soybean acres in location i at time t, $Yield_{i,t}$ is the bushels of soybeans per acre, SX_t is the USDA/RMA discovery price for time t, and *FungicideCost* refers to the \$22.49 per acre price of curative fungicide. The estimated actuarially-fair premium rates are presented in table 5. These rates are significantly different between the northern and southern U.S. regions, due to the significant differences in the probabilities of soybean rust infection.

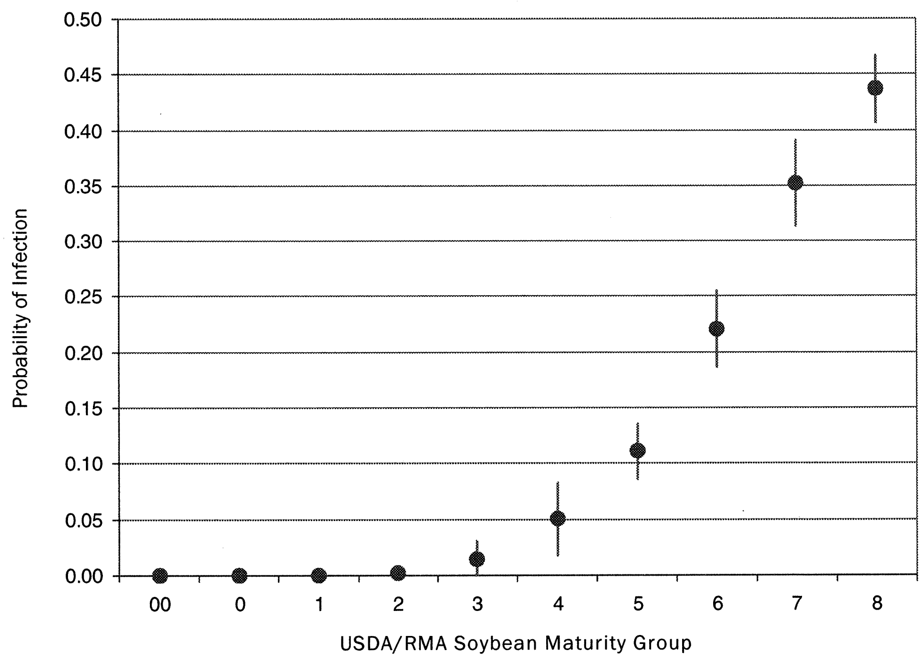
In the preferred ZINB model, the average premium rate for the most northern U.S. region (maturity groups 00–2) was less than 1%. In between the northern and southern United States (maturity groups 3–5), the average premium was 7.995%, but some were as low 1.24% and as high as 49.69%. Finally, in the most southern U.S. region (maturity groups 6–8), the average premium rate was 38.34%, ranging between 17.7% and 60.25%. These significant differences within and across regions reveal a substantial degree of spatial heterogeneity in the risks of soybean rust infection. Additionally, the uncertainty range for predicted probabilities is shown in figure 3. There is an exponential increase in infection probabilities across soybean maturity groups which, in general, represent the geographic locations of planted soybeans. The smallest uncertainty is in northern locations (maturity groups 00–2), which have an overall low probability of infection, and the most southern location (maturity group 8), because the favorable climatological factors for soybean rust survival reduce the uncertainty of infection. The greatest uncertainty exists in locations in which soybean rust infections are affected most by climatological patterns.

Moreover, as additional data about rust infection patterns become available, the calculated premium rates would require updating and are likely subject to change. The changes in the calculated probabilities can be greatly influenced by the potential for

[10] Under the construction of the insurance model discussed above, the estimated probability of infection is equal to the premium rate.

Table 5. Summary Statistics of Estimated Premium Rates for Soybean Rust Infections (7% loss coverage)

Model	Mean	Median	Std. Dev.	Minimum	Maximum
Maturity Groups 00–2:					
Probit	0.0154573	0.0150272	0.0028438	0.0017594	0.0215860
Poisson	0.0148683	0.0143680	0.0032405	0.0085818	0.0298839
Negative Binomial	0.0145988	0.0144856	0.0021095	0.0064503	0.0216479
ZIP	0.0000837	6.0252E-05	8.8292E-05	6.9949E-06	0.0008212
ZINB	7.5003E-05	6.5668E-05	4.2011E-05	1.9692E-06	0.0002984
Maturity Groups 3–5:					
Probit	0.1180732	0.1187277	0.0163185	0.0273520	0.1815636
Poisson	0.1615536	0.1533914	0.0456871	0.0920677	0.5307677
Negative Binomial	0.1346554	0.1313644	0.0259878	0.0652906	0.3664203
ZIP	0.0751452	0.0654753	0.0440742	0.0223005	0.4629237
ZINB	0.0799501	0.0728483	0.0419032	0.0123704	0.4969438
Maturity Groups 6–8:					
Probit	0.3587347	0.3483287	0.0589317	0.2124356	0.6087299
Poisson	0.4852171	0.4839556	0.0480797	0.3630430	0.5944294
Negative Binomial	0.3034229	0.2984571	0.0407754	0.1982414	0.5237806
ZIP	0.4154530	0.4116525	0.0532950	0.2790147	0.5892851
ZINB	0.3834445	0.3770635	0.0655046	0.1770288	0.6024985



Notes: Circles denote predicted probability; vertical lines denote ±2 * (Standard Error).

Figure 3. Estimated SBR infection probabilities by maturity group

continuing northward movement of soybean rust in the United States. Due to the ability of soybean rust to overwinter only in the southern and southeastern regions of the United States, the disease is reintroduced to the northern regions each planting season. The degree to which soybean rust moves north is determined by the amount of inoculum that accumulates during early spring in the southern United States. A spring season characterized by warm temperatures and significant precipitation could imply a faster and more intense accumulation of inoculum, thereby leading to a much higher probability for the spread of soybean rust into the North. This would increase the infection probabilities in the northern U.S. regions, and consequently raise premiums.

Conclusions and Policy Implications

In this analysis, we develop and evaluate several methods for modeling infection risk of soybean rust in the United States. The disease is highly infectious and can cause significant losses of soybean yields. Additionally, due to turbulent grain markets which have led to a significant rise in soybean prices, the potential for large economic losses due to SBR is accentuated. A brief overview of the disease as well as its pathological characteristics is provided, and climatological conditions are shown to be the primary factors in recognizing the ways that soybean rust spreads, germinates, and damages soybean plants. We also discuss the methodology by which we design an insurance policy that could be used to offer protection for U.S. soybean growers.

To ensure the insurance premium rates accurately reflect the risks associated with soybean rust infection, our analysis defines a single-peril insurance program that offers indemnity payments for damages related to soybean rust. A single-peril insurance policy overcomes a major disadvantage of a multiple-peril plan, which covers all losses that might be caused by a variety of hazards. Due to the extreme complexity of quantifying all possible risks associated with multiple-peril insurance coverage, premium rates based on aggregate risk measures are typically inaccurate. These rates often provide cheaper coverage for high-risk areas and more expensive coverage for low-risk locations. This skews insurance protection benefits, and consequently participation, in favor of high-risk growers. The empirical models used in this analysis provide explicit measures of soybean rust infection risks and the associated expected losses at the county level. These measures are then used to determine actuarially-fair premium rates that are appropriate for losses from soybean rust infection. The results reveal there might be significant differences in infection probabilities and associated premium rates among different locations.

Estimation of the infection risks and the associated premium rates was performed by using empirical models incorporating important spatio-temporal attributes of soybean rust. The likelihood of disease infection was shown to be significantly dependent on the infection status of neighboring locations and the infections in the previous period. To estimate the infection probabilities, we consider several econometric specifications that model the binary infection status and/or the count-data attributes of soybean rust infections. Further, due to the preponderance of observations where no infections were found, we consider "zero-inflated" alternatives of the typical count-data models. Lambert's (1992) zero-inflated Poisson (ZIP) and the zero-inflated negative binomial (ZINB) are two specifications used in this analysis. Additionally, we adjust for potential endogeneity between the number of inspections and the number of infections by introducing instrumental variables. This endogeneity might be caused by an increase in inspections by policy makers in areas having a large probability of infection.

The estimated actuarially-fair premium rates can be employed by U.S. policy makers to formulate an effective risk management program for U.S. soybean producers. Models used in this analysis differentiate infection risks according to regional climatological conditions, farming decisions, and production characteristics of specific counties. Knowledge of these factors can allow policy makers to assess and quantify the effects of each measure, and then develop specific mitigation efforts.

Based on the preferred ZINB model, average premium rates were 1.59% in northern U.S. regions, and 27.66% in the southern United States. Because soybean rust is a relatively new plant disease in the United States, current multiple-peril policies might not have adjusted their premium rates to reflect the risks associated with SBR. Accordingly, it is quite realistic to develop a single-peril insurance plan that would offer these actuarially-fair and cost-effective premiums for indemnities paid due to soybean rust infection. However, as additional data about the overwinterization and spread patterns of soybean rust in the United States become available, premiums should be updated to reflect accurate infection probabilities. Knowledge about the behavior of inoculum accumulation in the southern U.S. region during early spring can lead to more precise measurements of infection susceptibility and premiums in northern U.S. regions.

Future work on this topic might include a comparison of additional models that can be used for analysis of panel data. For example, it can be useful to consider other specifications such as a random-effects model.[11] A straightforward application of this model is beyond the scope of our analysis for several important reasons. First, the data suggest that we not only use a limited dependent variable model, but require a regime switching structure to account for the preponderance-of-zeros problem previously discussed. Next, due to the randomness of infection behavior by invasive species, in general, it is almost never possible to attain a balanced panel data set. The use of an unbalanced data set creates additional specification issues. Finally, using a standard random-effects model restricts the out-of-sample predictions to only counties that are included in the sample. Although appropriately addressing these concerns is outside the realm of this study, such extensions form an important basis for future work.

[*Received March 2008; final revision received October 2008.*]

References

Akinsanmi, A., and J. Ladipo. "First Report of Soybean Rust in Nigeria." *Plant Discovery* 85(2001):87.

American Phytopathological Society. "National Soybean Rust Symposium" [discussion of proceedings]. APS, St. Louis, MO, 2006.

Bromfeld, K., M. Bonde, and J. Melching. "Histology of the Suscept-Pathogen Relationship Between *Glycine max* and *Phakopsora pachyrhizi*, the Cause of Soybean Rust." *J. Phytopathology* 66(1976): 1290–1294.

Brown, J., and M. Hovmeller. "Aerial Dispersal of Pathogens on the Global and Continental Scales and Its Impact on Plant Disease." *Science's Compass* 297(2002):537–540.

Caldwell, P., and M. Laing. "Soybean Rust: A New Disease on the Move." Unpub. manu., 2001. Online. Available at http://www.saspp.co.za.

[11] We are grateful to an anonymous referee for the suggestion of implementing this model.

Carlstein, E. "The Use of Subseries Methods for Estimating the Variance of a General Statistic from a Stationary Time Series." *Annals of Statistics* 14(1986):1171–1179.

Chen, C. "Evaluation of Soybean Rust Tolerance at Hualien." *Soybean Rust Newsletter* 9(1989):4–5.

Coastal Agribusiness. Data on fungicide costs. Carthage, NC, 2008.

Dufresne, L., and G. Bean. "Effects of Temperature and Light Intensity on Telia Development by Puerto Rico and Taiwan Isolates of *Phakopsora pachyrhizi*, the Soybean Rust Fungus." *Plant Disease* 71(July 1987):629–631.

Dunphy, J. Professor, Department of Crop Science, North Carolina State University, Raleigh. Personal telephone contact regarding soybean rust, 2007.

Heilbron, D. "Generalized Linear Models for Altered Zero Probabilities and Overdispersion in Count Data." Technical Report, Dept. of Epidemiology and Biostatistics, University of California, San Francisco, 1989.

Johnson, N., S. Kotz, and A. Kemp, eds. *Distributions in Statistics—Univariate Discrete Distributions*, 2nd ed. New York: John Wiley and Sons, 1993.

Kim, H., and S. Shanmugasundaram. "Inference of Plant Population Density on the Incidence of Soybean Rust." *Soybean Rust Newsletter* 2(1979):23.

Lambert, D. "Zero-Inflated Poisson Regression, with an Application to Defects in Manufacturing." *Technometrics* 34(1992):1–14.

Livingston, M., M. Roberts, M. Johansson, R. Daberkow, M. Ash, and V. Breneman. "Economic and Policy Implications of Wind-Borne Entry of Asian Soybean Rust into the United States." USDA/ERS, Washington, DC, 2004. Online. Available at http://www.ers.usda.gov/publications/OCS/APR04/OCS04D02/.

McWilliams, D., D. Bergland, and G. Endres. "Soybean Growth and Management: Quick Guide." North Dakota State University Ext. Ser., Fargo, 1999. Online. Available at http://www.ag.ndsu.edu/pubs/plantsci/rowcrops/a1174/a1174.pdf.

Pretorius, A. "First Report of Soybean Rust in South Africa." *Plant Discovery* 85(2001):1288.

Roberts, M., D. Schimmelpfennig, E. Ashley, and M. Livingston. "The Value of Plant Disease Early-Warning Systems: A Case Study of USDA's Soybean Rust Coordinated Framework." USDA/ERS, Washington, DC, 2006. Online. Available at http://www.ers.usda.gov/publications/err18/err18fm.pdf.

Saksirirat, W., and H. Hoppe. "Teliospore Germination of Soybean Rust Fungus." *J. Phytopathology* 132(1991):339–342.

Sinclair, J. B., and G. L. Hartman, eds. *Proceedings of the Soybean Rust Workshop.* National Soybean Research Laboratory, University of Illinois at Urbana-Champaign, 1995.

Sinclair, J. B., G. L. Hartman, and J. C. Rupe, eds. *Compendium of Soybean Diseases.* St. Paul, MN: American Phytopathological Society, 1999.

Tschanz, A., and B. Tsai. "Effect of Maturity on Soybean Rust Development." *Soybean Rust Newsletter* 5(1982):38–41.

U.S. Department of Agriculture, Agricultural Research Service. *Proceedings of the Workshop on Soybean Rust in the Western Hemisphere.* USDA/ARS, Washington, DC, 1976.

U.S. Department of Agriculture, Risk Management Agency. "Commodities Recently in Discovery." USDA/RMA, Washington, DC, 2008. Online. Available at http://www3.rma.usda.gov/apps/price discoveryweb/CropsInDiscovery.aspx.

Vuong, Q. "Likelihood Ratio Tests for Model Selection and Non-Nested Hypotheses." *Econometrica* 57(1989):307–333.

Yang, X., and W. Batchelor. "Modeling Plant Disease Dynamics Using Neural Networks." *Plant Disease Forecasting* 11(1997):47–55.