Spatio-temporal Risk and Severity Analysis of Soybean Rust in the U.S.

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

(Abbreviated Title: Spatio-temporal Risk Analysis of Soybean Rust)

* Anton Bekkerman is a graduate student in the Department of Agricultural and Resource Economics at North Carolina State University. Barry K. Goodwin is a William Neal Reynolds Professor in the Departments of Agricultural and Resource Economics at North Carolina State University. Nicholas E. Piggott is an associate professor in the Department of Agricultural and Resource Economics at North Carolina State University. Direct correspondence to Anton Bekkerman, North Carolina State University, Box 8109, Raleigh NC, 27695, USA.
Email: abekker@ncsu.edu

Abstract

Soybean rust (Phakopsora pachyrhizi) is an infectious disease that is highly mobile and can be transmitted across short and long distances. Soybean rust is estimated to cause yield losses that can range between 1%-25%. To analyze the economic impacts of SBR within the U.S., a unique data set is used to examine the spatio-temporal risks and severity of soybean rust infections. Using observations that were collected from over 35,000 field-level inspections between 2005 and 2007, a county-level analysis is conducted. Statistical inferences are derived by using 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 aspects for determining soybean rust. These results are then used to accordingly price annual insurance contracts that cover soybean rust damages.

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

JEL classification codes: Q18, Q19

Spatio-temporal Risk and Severity Analysis of Soybean Rust in the U.S.

The U.S. soybean sector has avoided an onset of soybean rust (SBR) for over a century, while other major world producers endured considerable yield losses, which ranged between 10%-90%, due to this highly infectious disease (Akinsanmi and Ladipo 2001, Caldwell and Laing 2001, Bromfield, Bonde, and Melching 1976, Chen 1989). In the U.S., Roberts et al. (2006) reports 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 that is 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 U.S. due to soybean rust can range from $630 million to $1.3 billion, and during the National Soybean Rust Symposium (APS 2006) it was suggested that a typical 800-1,000 acre soybean farm will have a $20,000 - $30,000 loss. However, at the current market conditions in which prices of soybeans have more than doubled over the past year, the economic impacts of soybean rust can be dire.

In 2007-08, over 63.6 million acres of soybeans were planted in the U.S., which is an 11.9 million acre decline from the previous season. This significant decrease in soybean acreage, along with a slight reduction in 2007-08 yields, has led to a 13% drop in the supply of soybeans. Despite the lower supply and substantially higher prices, the demand and total use of soybeans remained relatively constant, which has resulted in an almost 70% decline in the 2007-08 ending stocks of soybeans. Additionally, during January and February of 2008, the new crop soybeans futures steadily rose from $11/bushel to $14/bushel, which implies an average value of

[1] The U.S. has produced an average of 2.945 billion bushels and exported an average of 40% of the worlds soybeans between 2005 and 2007.

\$600/acre for 2008-09 soybeans.[2] Ultimately, the tightening of soybean stocks, higher new crops prices, and concerns that a significant increase of soybean rust infections in 2007-08 might affect soybean yields in 2008-09, has led to a heated bidding war for 2008-09 acreage between the corn and soybean markets.

Soybean rust (*Phakopsora pachyrhizi*) is a fungal disease that can spread rapidly across long and short distances (Brown and Hovmeller 2002). The disease causes tan lesions on a plant's leaf (NSRL 1995) and leads to premature defoliation (Dunphy 2007, Pretorius 2001). In the U.S., soybean rust was first detected in Florida in 2004, which prompted an inspection and tracking program by the USDA (USDA-APHIS). In the following years, incidents of soybean rust infections have been frequently reported further west and northwest – regions of major soybean production. Since soybean rust has over 34 natural hosts, including common weeds such as kudzu (APS 1999), and winter climatological conditions in the southeastern U.S. are favorable for soybean rust survival (Livingston, Roberts, Johansson, Daberkow, Ash, and Breneman 2004, NSRL 1995), the disease appears to be a long-term concern for U.S. farmers.

The transmission of soybean rust occurs when postules from already developed lesions are carried by wind and rain to other locations. Typically, symptoms of rust can be seen between 3-7 days after infection (ARS-USDA 1976), and soybean plants can be infected at any growth stage (Dufresne and Bean 1987). Due to the quickly spreading and highly infectious characteristics 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.

The introduction of soybean rust within the U.S. and the infection tracking

[2] Based on an average of 43 bushels per acre.

program enacted by the USDA present an ideal opportunity for a study that models soybean rust infection risk in the U.S. Extensive farm-level information collected by the tracking program is combined with detailed data about climatological and biological factors to investigate the underlying risks of SBR spread. Using over 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 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 agricultural insurance policies. These specific-peril insurance plans can be used as additional or alternative methods of protection for soybean growers in case of economic losses due to soybean rust infections. The following sections present a detailed overview of the pathological attributes of soybean rust, potential impacts of infection, empirical models and results, and estimates of premium rates for annual insurance contracts.

Soybean Rust

In order to develop a model that can accurately describe the spatial and temporal infection risks of soybean rust, it is necessary to consider the pathological properties of the disease. Since soybean rust has been a factor in agricultural economies outside of the U.S. for over a century, there has been a significant amount of biological research that has studied infection and transmission attributes of soybean rust. For our analysis, it is useful to employ this existing research in order to understand important pathological aspects of the disease and how they influence the spatial and temporal patterns of infection. It should be noted that, although many of the pathological studies focused on small scale controlled experiments and arrived at specific outcomes about the disease, we use these results as a foundation for determining factors that might affect the spread of the disease on larger scale (for example, across counties).

Soybean rust is a fungal plant disease that belongs to the "obligately biotrophic" fungi family. The disease is dependent on living tissue (Brown and Hovmeller 2002), affecting the leaves of a living plant. Common symptoms of soybean rust include tan and dark brown lesions with a central opening (SBR Workshop 1995). These lesions spread throughout the green surface of a leaf, causing a smaller area for the occurrence of photosynthesis. Eventually, the fungus causes early defoliation, formation of new postules that can spread to other leafs, destruction of the leaf chlorophyll, and death of the plant (Dufresne and Bean 1987). The consequences of the disease are fewer soybean plants per acre, less pods per plant, smaller pods, and a reduced number of seeds per pod – all of which imply lower yields (Dunphy 2007).

Plants are infected with soybean rust when spores of the disease land on the leaf of the plant. Symptoms of the infection typically occur 4-5 days after inoculation, postules can be seen 7-10 days after infection, and new spores that can spread to other plants form within 2-3 weeks (APS 2006). Infection occurs very quickly, and under normal climatological conditions, typical infection can occur in 4 to 12 hours (Marchetti, Melching, and Bromfield 1976). Dufresne and Bean (1987) notes that the infection of a soybean plant can occur at any stage of the plant's growth. However, plants that are infected early in their life are much more susceptible to increased damages (Dunphy 2007). It is important to note that soybean rust cannot be transmitted in plant seeds or in the soil of infected plants. Yeh, Sinclair, and Tschanz (1982) and Brown and Hovmeller (2002) point out that the fungi is unable to survive in non-living plant debris, soil between plantings, and plant roots.

Although soybean rust is highly susceptible to the fate of its host, a key aspect of this disease is its rapid dispersion across a vast space. This requires that when modeling the risks of soybean rust infection, it is necessary to control for the correlation of risks across space. As Brown and Hovmeller (2002) describes, the primary survival strategy of a fungal disease is long and short distance dispersal. In modeling the spatial infection risks, it is intuitive to assume that distance and risk have an inverse relationship. However, the factors that are most influential in determining the spatial transmission of SBR are climatological. This implies that accurately modeling the spatial aspects of infection risks requires knowledge about the interaction of weather-related factors and infection probabilities.

In general, there are four aspects that have been found to significantly affect the spread and germination of soybean rust. Wind and precipitation allow rust to be carried between different locations, and warm temperatures and high moisture levels increase the probability of infection. In our analysis, determining factors that affect the transmission of soybean rust across space would increase the accuracy of modeling risk probabilities. Isard, Comtois, and Russo (2005) predicted that soybean rust was carried to the U.S. from either Africa or South America by tropical storms, and in general, the frequency and quantity of rainfall is a primary factor infection rates (APS 2006). After the fungal spores are transmitted between locations, germination of the disease is almost entirely dependent on the wetness of the leaf and the air temperature. For spore germination to occur, only 3 to 6 hours of leaf wetness (typical morning dew) is required (APS 2006), while maximum infection takes place if a host leaf is wet for over 10 hours (Marchetti, Melching, and Bromfield 1976). This implies that precipitation is an integral factor for modeling infection risk, since it is not only a catalyst for disease transport, but also an important aspect of SBR germination. Thus, accurately determining the patterns of precipitation between infected and non-infected locations would greatly aid in appropriately modeling the spatial correlation of soybean rust risks.

Survival of soybean rust from one season to the next is highly dependent on the life of the host plant. 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). So, host plants that are located in areas with temperate winter climates provide an opportunity for soybean rust to survive during the winter months. The Southeastern U.S., which often has year-round above-freezing temperatures, high moisture levels, and prevalence of kudzu, presents optimal conditions for soybean rust to remain an annual, long-term concern for soybean growers. Thus, tracking the survival of soybean rust requires examining the interaction of climatological patterns during a soybean growing-season, which might increase the probability of rust infection, as well as the overwinterization attributes that can raise SBR survival rates.

In addition to climatological aspects, previous research has pointed to other important factors that affect the probability of soybean rust infection. In studying the attributes that are relevant to soybean rust transmission, Yang (1997) finds that relative humidity and temperatures have large impacts on determining the spread of the disease. Roberts et al. (2006) points out that planting dates of soybeans has a significant effect on rust probabilities, while Tschanz and Tsai (1982) finds that 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 of soybean rust is currently limited to the application of fungicide.

Tschanz, Wang, and Hu (1980) finds that one of the most important factors in the development of rust after infection is the use of fungicide. Livingston et al. (2004) study yield losses from soybean rust in Brazil and Paraguay. They find that application of fungicide after infection resulted in a 4.3% yield loss, while no fungicide use caused a 25% reduction in yields. Roberts et al. (2006) consider several types of fungicide applications to predict potential soybean rust effects in the U.S. The authors determine that applying preventive fungicide, which is most expensive, would lead to only a 1% yield loss if soybean rust infection occurred. If a less expensive curative fungicide is used after an infection is found, expected yield losses are approximately 7%. However, if no fungicide is used, growers may incur up to a 25% loss. Table 1 presents potential losses in 2008-09 under the various fungicide application scenarios.

Model

In developing an insurance contract that addresses 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. Many yield, price, and revenue insurance plans often cannot appropriately measure all of the risks that 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 that are based only on the factors and risks that are 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 to design a specific peril insurance contract for soybean rust that minimizes the shortcomings that are associated with all-risk contracts.

An integral issue with 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 that are paid out relative to the total premiums that are collected. In order to preserve a relative equality between indemnities and premiums, it is necessary to determine 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 and the worst-case scenario loss that the farmer would incur due to the disease under the terms of the insurance plan.

To charge the appropriate premium rate, an insurance plan must determine and model the risks that are associated with a particular hazard, in order to ensure that 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, leaving a smaller, more risky pool of insurance-purchasing farmers. Conversely, premium rates that are set too low result in indemnity payouts that are not matched by the premium payments. This phenomenon is referred to as adverse selection. Deriving an actuarially-fair rate involves modeling risks using a conditional probability density function that describes the outcomes, if a hazardous event occurs. Suppose that 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:

$$\text{Indemnity}_{i,t} = \text{Price}_t \cdot max\{0,\ \theta\mu - y_{i,t}\} \tag{1}$$

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 that 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:

$$E[\ Loss\ ]_{i,t} = Pr[y_{i,t} < \theta\mu] \cdot (\theta\mu - E[y_{i,t} \mid y_{i,t} < \theta\mu]) \tag{2}$$

To solve for the expected losses, let $f(y)$ represent the probability density function of the yields, and compute the following:

$$E[\ Loss\ ]_{i,t} = \int_0^{\theta\mu} f(y)dy \left(\theta\mu - \frac{\int_0^{\theta\mu} y_{i,t} \cdot f(y)dy}{\int_0^{\theta\mu} f(y)dy} \right) \tag{3}$$

In the case of soybean rust, which spreads quickly from one host to another and there is certainty infection, a farm that is infected has a high probability of at least some loss. For an insurance contract, this implies that a loss event will trigger a payment of some pre-determined fixed indemnity payment. In such a case, the expected loss is the product of the probability of loss and total payment that is made in the event of a loss, and the premium rate is the probability of a loss. Respectively,

$$E[\ Loss\ ]_{i,t} = Pr[y_{i,t} < \theta\mu] \cdot \theta\mu \tag{4}$$

$$\text{Rate}_{i,t} = Pr[y_{i,t} < \theta\mu] \tag{5}$$

where the total payment is fixed in order to cover the fixed percentage of yield loss and the cost of curative fungicide treatment. This is expressed as $\theta\mu = \overline{P}$, such that $\overline{P}$ is a fixed payment per acre that is independent of the degree of actual losses suffered from an infection.

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 that are double-cropped with wheat are often more susceptible to soybean rust because they are planted later in the planting 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 that has been found to be an important element in influencing infection risk is the choice of the soybean maturity group. Insurance contracts that identify deterministic factors produce more precise and actuarially fair premium rates.

Another issue that is important 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 that is 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, it 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. For example, knowing that in the previous year a particular area had heavy rains and high winds, 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 the principal knows 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 a 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 that are 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 an infection. Since 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 that can successfully capture these characteristics involves conditioning soybean rust infection at a particular location on historical infection status in nearby locations. Such a conditional probability of infection is given by:

$$Pr[S_{i,t}] = f(S_{i,t} \mid S_{j,t-1}, S_{k,t-1}, \ldots, Z_{i,t}) + \varepsilon_{i,t} \quad (6)$$

where $S_{i,t}$ corresponds to at least one soybean rust infection in location i during time t, $S_{j,t-1}$ is at least one soybean rust infection 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. Neighboring counties are those that are connected by a common border, a major road, a body of water, or if the counties meet at a corner. The random error term is $\varepsilon_{i,t}$.

Empirical Framework

Data

This analysis uses farm-level inspection data, which is collected by the USDA, the National Plant Diagnostic Network (NPDN), and the National Agricultural Pest Information System (NAPIS). Inspection observations range between January, 2005 and November, 2007. Weather statistics for the same time period are 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 collected from various sources, including NASS-USDA and RMA-USDA. The data consists 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 study is at the county level. Although the data 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 applicable in modeling infection risk and constructing an insurance contract. This is the case for several reasons. First, unlike other diseases, soybean rust does not differentiate between different soybean cultivars, which implies that under certain climatological conditions that were mentioned previously, rust can occur at any farm in the county. Second, because soybean rust is highly contagious and easily transmitted, there is a larger probability that farms in the same county will be infected. Lastly, determining insurance premiums at the county level allows the smoothing of premium rates across individual farms, which is advantageous for insurance providers. Since premium rates are homogenous across the county, it would be possible to calculate accurate rates without excessive costs.

Econometric Specification

In modeling the risk of soybean rust infection, it is necessary to apply the conditional probability described in equation (6) to the available data. This article considers several approaches to model this risk in an effort to appropriately 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. In this case,

$$Pr[S_{i,t} = s_{i,t}|\mathbf{x}_{i,t}] = I\{s_{i,t} > 0\} \cdot \Phi(\mathbf{x}'_{i,t}\beta) + I\{s_{i,t} = 0\} \cdot (1 - \Phi(\mathbf{x}'_{i,t}\beta)) \tag{7}$$

where $\mathbf{x}$ is a vector of covariates, β is a vector of estimable parameters, and $I\{\cdot\}$ is an indicator function.

Alternatively, it is possible to use count-data models to measure the number of soybean rust infections in a particular inspected county. This study considers 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. The Poisson model used for modeling the infection counts in a county is as follows:

$$Pr[S_{i,t} = s_{i,t}|\mathbf{x}_{i,t}] = \frac{e^{-\lambda_{i,t}}\lambda_{i,t}^{s_{i,t}}}{s_{i,t}!} \tag{8}$$

where $\lambda_{i,t} = \exp(\mathbf{x}'_{i,t}\beta)$, and β is a vector of estimable parameters. Similarly, the negative binomial representation is given by:

$$Pr[S_{i,t} = s_{i,t}|\mathbf{x}_{i,t}] = \left[\frac{\Gamma(s_{i,t} + \frac{1}{\kappa})}{\Gamma(s_{i,t} + 1)\Gamma(\frac{1}{\kappa})}\right] \frac{(\kappa\mu_{i,t})^{s_{i,t}}}{(1 + \kappa\mu_{i,t})^{s_{i,t}+1/\kappa}} \tag{9}$$

where $\mu_{i,t} = \exp(\mathbf{x}'_{i,t}\beta)$, and κ is the coefficient of overdispersion. As the coefficient of overdispersion decreases to zero, the negative binomial model collapses to a Poisson specification. A likelihood ratio test can be performed to test the null hypothesis, $\kappa = 0$.

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 still a preponderance of observations for which no rust was found. This characteristic of the data is illustrated in Figure 1. This might imply that observations with no rust finds come from a data generating process that is neither Poisson nor negative binomial. Without capturing the different data generating processes, modeling the entire data by using a single specification can lead to inaccurate parameter estimates and inappropriate inferences.

Previous research indicates that regime switching-type models or mixture models provide a more accurate representation of the zero and non-zero outcomes (for example, see Heilbron (1989), Lambert (1992), and Johnson, Kotz, and Kemp

(1993)). These mixture models first capture the probability of an outcome to be non-zero, and then represent the non-zero 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 non-zero 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 zero-inflated Poisson (ZIP) is as follows:

$$
\begin{aligned}
Pr[S_{i,t} = 0|\mathbf{w}_{i,t}] &= (1 - \Phi(\mathbf{w}'_{i,t}\gamma)) + \Phi(\mathbf{w}'_{i,t}\gamma) \cdot e^{-\lambda_{i,t}} \\
Pr[S_{i,t} = s_{i,t}|\mathbf{x}_{i,t}] &= \Phi(\mathbf{w}'_{i,t}\gamma) \cdot \frac{e^{-\lambda_{i,t}}\lambda_{i,t}^{s_{i,t}}}{s_{i,t}!}, \quad \text{for } s_{i,t} \geq 1
\end{aligned} \tag{10}
$$

where $\mathbf{w}_{i,t}$ is a vector of covariates that determines the probability of infection, $\mathbf{x}_{i,t}$ is a vector of covariates that is relevant to the number of infections in a county that has at least one infection, and γ is a vector of estimable parameters. Similarly, the zero-inflated negative binomial (ZINB) is given by:

$$
\begin{aligned}
Pr[S_{i,t} = 0|\mathbf{w}_{i,t}] &= (1 - \Phi(\mathbf{w}'_{i,t}\gamma)) + \Phi(\mathbf{w}'_{i,t}\gamma) \cdot \left[\frac{1}{(1+\kappa\mu_{i,t})^{1/\kappa}}\right] \\
Pr[S_{i,t} = s_{i,t}|\mathbf{x}_{i,t}] &= \Phi(\mathbf{w}'_{i,t}\gamma) \cdot \left\{\left[\frac{\Gamma(s_{i,t}+\frac{1}{\kappa})}{\Gamma(s_{i,t}+1)\Gamma(\frac{1}{\kappa})}\right] \frac{(\kappa\mu_{i,t})^{s_{i,t}}}{(1+\kappa\mu_{i,t})^{s_{i,t}+1/\kappa}}\right\}
\end{aligned} \tag{11}
$$

The covariates that are 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 the risks of soybean rust infections. Primarily, this is related to the pathological characteristics of the soybean rust. In general, there are three important categories that are addressed with the choice of the covariates: the ability for rust to be transferred from one county to another; the conditions that allow rust to reappear in the next year; and, 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. For example, a county that has had 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 have an increased chance of developing rust in the next season.

One issue that requires additional attention is the possibility of dependence between the soybean rust finds and the variable that measures the number of inspections. Since observing a rust infection is wholly dependent on an inspection, it is expected that finding more infections in a given year will trigger an increased number of inspections in the following year.[3] This is the case in our data, which shows that 25% of the counties had more soybean rust infections than in the previous year, and, on average, there were over two additional inspections in the following year within those counties. This dependence implies that there might be endogeneity between the number of positive soybean rust observations and the number of inspections. In other words, rust infections at time t are a function of inspections at time t, which is a function of rust infections at time $t-1$. This

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

relationship is given by:

$$\text{SBR Infections}_{i,t} = f(\text{Inspections}_{i,t})$$

$$\text{and} \tag{12}$$

$$\text{Inspections}_{i,t} = g(\text{SBR Infections}_{i,t-1})$$

where $\texttt{cov}[\ (\text{SBR Infections}_{i,t}), (\text{SBR Infections}_{i,t-1})\ ] \neq 0$. To address this endogeneity, we estimate two-stage models, where the first stage employs instrumental variables to derive inspections in year t, and the second stage uses the binary or count-data specifications. Ordinary least squares (OLS) is used to estimate the first stage, and a maximum likelihood procedure is implemented for each second-stage specification. To derive a consistent estimate of the covariance matrix for the parameters of the IV estimation, we use a bootstrap procedure. Specifically, we randomly sampled with replacement from our data set, and for each replication parameters were estimated. Using 5,000 replicated parameter estimates, consistent standard errors were calculated.

One additional issue that was considered is the potential presence of spatial autocorrelation in the estimated residuals. Since we are modeling data that has a spatial dimension, it is necessary to correct for the spatial autocorrelation that might reflect the effects of omitted spatially correlated variables. Although there are non-structural 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 a "moving block bootstrapping" procedure proposed by Künsch (1989), Hall (1985), and Liu and Singh (1992). This technique involves randomly selecting an individual observation, and then adding all other points that fall within the same time period and spatial block, l. In our model, each l^{th} block consists of observations that are within the same agricultural statistical district of the randomly selected observation.[4]

Empirical Results and Analysis

The results of each specification are used as 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. As a baseline measurement, historical means are used to determine the infection probabilities. The infection probabilities are shown in Figure 2. However, the historical infection probabilities ignore a multitude of important factors that significantly affect the spread and survival of soybean rust infections.

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). Specifically, it was shown that climatological factors such as wind speeds, precipitation, and relative humidity, as well as overwintering temperatures are contributors to infection risk. Additionally, the planting date of the soybean crop, and its maturity group are also important for understanding the effects of soybean rust. Table 2 presents the summary statistics and descriptions of variables that are used to model infection risks.

[4]Agricultural statistical districts are defined by USDA-NASS.

As discussed above, there is concern of endogeneity between the number of inspections and the number of detected soybean rust infections. To address this issue, we use instrumental variables (IV) to model inspections, and then use the estimates to construct an uncorrelated predicted inspections variable within the specifications that model rust infections. Ordinary least squares are used to estimate inspections as a function of expected farm income, the proportion of soybeans planted to other grains planted in the previous period, and the number of inspections in the previous that did not find soybean rust. Bootstrapping is used to derive a consistent covariance matrix for the IV estimates.

Using the results from the IV model, a simple probit model was used 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 estimates indicate that only the infections in the previous year, the 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 inverse relationship between infections in the current and previous years suggests that a location could be more susceptible to soybean rust if there is historical evidence of infection. The harvested-to-planted coefficient seems to indicate that a county that has more soybean acres (and accordingly more hosts) might be more susceptible to soybean rust infection. These findings are consistent with past epidemiological studies (for example, see Kim and Shanmugasundaram 1979). Finally, even though all soybean varieties are susceptible to rust, the maturity group coefficient appropriately indicates that later-maturing soybeans tend to be 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 that are identified with a higher maturity group are typically grown in the southern U.S., 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 that soybean rust can affect locations that are near already infected areas, historically infected 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 indicate similar patterns of infection risk, which is mostly concentrated in the southeastern U.S. and the Mississippi delta. However, the results also indicate a significant probability of infection in the Mid-West and Great Plains regions.

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 and negative binomial specifications. The estimation of the zero-inflated models is performed using the maximum likelihood approach, and the results are listed in Table 3 and Table 4.

These models provide a much richer understanding of the effects that important spatial, temporal, and biological factors on soybean rust infection probabilities.

Generally, the coefficients in the two specifications indicate similar expected 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 that there might be a 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 one-percent increase in infections during t implies a 0.21% (ZIP) and 0.02% (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 that describes the interaction between the precipitation in $t-1$ and overwintering temperature implies a 0.495% increase in the probability of soybean rust infection. Similarly, infection probability rises if there are higher wind speeds and temperate overwintering temperatures.

When comparing the two models, it is often useful to examine the coefficient of overdispersion. As the coefficient converges to zero, the zero-inflated negative binomial specification becomes the zero-inflated Poisson. In our results, the coefficient is significantly different from zero, which might suggest that the ZINB specification is more appropriate for the data. Similarly, information criteria measures such as AIC and SBC indicate that the ZINB provides a better fit than the ZIP model. For the ZINB model, the predicted probabilities are presented in Figure 3. As do all of the specifications, both of these models indicate a high probabilities of infection in the South and Southeastern U.S. These results confirm outcomes of past studies, which show that optimal conditions for soybean rust are 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 re-estimate the models using a moving block bootstrap procedure. In general, the results are quite similar to those that were estimated without the block bootstrap. The results of the zero-inflated negative binomial specifications are presented in Table 5.[5] One major difference, which was typical in each block bootstrapped model, is the statistical insignificance of the nearby infections coefficient. This might imply that directly controlling for 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 moving block bootstrap, this particular variable becomes insignificant.

Insurance Premiums

The overall goal of the preceding analysis is to construct models that can measure the risk of a soybean rust infection, and then use these probabilities to determine actuarially-fair insurance 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 as follows:

[5] Only the ZINB results are presented; however, the implications of this model are typical across all of the specifications in this analysis.

$$E[\ Loss\ ]_{i,t} = Pr[\ \text{County}_{i,t} = \text{Infected}|X_{i,t}\ ] \cdot Payment \tag{13}$$

where the infection status in county i at time t is conditioned on covariates $X_{i,t}$. An equivalent representation of equation (13) is given by:

$$E[\ Loss\ ]_{i,t} = F_{i,t}(X\beta) \cdot Payment \tag{14}$$

where $F_{i,t}(\cdot)$ are measures of conditional infection risk that are determined by each empirical specification. The *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 in Roberts et al (2006). The authors describe potential yield losses as a function of fungicide application. If preventive fungicide is applied, then the predicted losses due to soybean rust is estimated to be approximately 1%. Applying curative fungicide would result in approximately a 7% yield loss. And, if no fungicide is used, then the authors predict up to a 25% loss. We assume that 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 growers within the county, regardless of whether a grower has reported an infection or not (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. The new crop discovery prices are intended to be used for revenue insurance products, which depend on November soybean futures. So, for our analysis *Payment* for county i is expressed as:

$$Payment = (\text{Acres})_{i,t-1} \cdot \{(\text{Bushels}_{i,t-1}\text{Percentage Lost}) \cdot SX_t + \text{Fungicide Cost}\} \tag{15}$$

where $\text{Acres}_{i,t-1}$ corresponds to the planted soybeans acres in location i at time $t-1$, $\text{Bushels}_{i,t-1}$ is the bushels of soybeans per acre, SX_t is the USDA-RMA discovery price for time t, and Fungicide Cost refers to the \$13.81 per acre price of curative fungicide. The estimated premiums rates are presented in Table 6. These premium rates are significantly different between the northern U.S. and southern U.S. regions, due to the significant differences in the probabilities of soybean rust infection. This suggests that the accuracy of premiums rates strongly depends on location.

In the preferred ZINB model, the average premium for Northern U.S. was 1.59%, and ranged from 0% to 33.35%. In the Southern U.S., the average premium was 27.66%, but some premiums were as low 5.96% and as high as 51.02%. These significant differences within and across regions reveal a substantial degree of spatial heterogeneity in the risks of soybean rust infection. Moreover, as additional data about rust infection patterns becomes available, the calculated premiums would require updating and are likely subject to change. These changes are due to the northward movement of soybean rust in the U.S., which increases the infection probabilities in the Northern U.S. regions, and accordingly, raises premiums.

Conclusions and Policy Implications

In this analysis, we develop and evaluate several methods for modeling infection risk of soybean rust in the U.S. The disease is highly infectious, easily transmittable, 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 quite high. A brief overview of the disease as well as its pathological characteristics are provided, and climatological conditions are shown to be the primary factors in recognizing the ways that soybean rust spreads, germinates, and damages soybean plants. Next, we discuss the methodology by which we design an insurance policy that could be used to offer protection for U.S. soybean growers.

To ensure that the insurance premium rates accurately reflect the risks that are associated with soybean rust infection, our analysis defines a single-peril insurance program that would offer indemnity payments for damages that are 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 that are associated with multiple-peril insurance coverage, the premium rates that are 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, which skews insurance protection benefits in favor of high risk growers. The empirical models that are 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 indicate that 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 that incorporated 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. In addition, due to the preponderance of observations where no infections were found, we consider "zero-inflated" alternatives of the typical count-data models. The zero-inflated Poisson (ZIP) of Lambert (1992) and the zero-inflated negative binomial are two specifications that are used. 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 policymakers increasing inspections in areas that have a large probability of infection.

The estimated actuarially-fair premium rates can be used by U.S. policymakers to formulate an effective risk management program for U.S. soybean producers. Models that are used in this analysis differentiate infection risks according to regional climatological conditions, farming decisions, and production characteristics of specific counties. Knowledge of these can allow policymakers to assess and quantify the effects of each factor, 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 U.S. Due to the fact that soybean rust is a relatively new plant disease in the U.S., current multiple-peril policies might not have adjusted their premium rates to reflect the risks that are associated with SBR. This implies that it is quite realistic to develop a single-peril insurance plan that would offer these actuarially-fair and cost-effective premiums for indemnities that are paid due to soybean rust infection. However, as additional data about soybean rust infections in the U.S. becomes available, premiums should be updated to reflect accurate infection probabilities. This is especially true for the Northern U.S. regions, which can become much more susceptible to infections as rust moves further north.

References

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

APS. 1999. "Compendium of Soybean Diseases." J.B. Sinclair and G.L. Hartman and J.C. Rupe, editors.

—. 2006. "National Soybean Rust Symposium." American Phytopathological Society.

ARS-USDA. 1976. "Proceedings of the Workshop on Soybean Rust in the Western Hemisphere."

Bromfield, K., M. Bonde, and J. Melching. 1976. "Histology of the suscept-pathogen relationship between Glycine max and Phakopsora pachyrhizi, the cause of soybean rust." *Journal of Phytopathology* 66:1290–1294.

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

Caldwell, P., and M. Laing. 2001. "Soybean rust – A New Disease on the Move." Unpublished, http://www.saspp.co.za.

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

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

Dunphy, J. 2007. From telephone conversation.

Hall, P. 1985. "Resampling a coverage pattern." *Stochastic Processes and Applications* 20:231–246.

Heilbron, D. 1989. "Generalized Linear Models for Altered Zero Probabilities and Overdispersion in Count Data." Technical Report.

Isard, S., S. Comtois, and J. Russo. 2005. "Principles of aerobiology applied to soybean rust as an invasive species." *BioScience* 55:851–862.

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

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

Künsch, H. 1989. "The jackknife and the bootstrap for general stationary observations." *Annuls of Statistics* 17:1217–1241.

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

Liu, R., and K. Singh, eds. 1992. *Moving blocks jackknife and bootstrap capture weak dependence*. Exploring the Limits of Bootstrap, Wiley, New York, R. LePage and L. Billard, eds.

Livingston, M., M. Roberts, M. Johansson, R. Daberkow, M. Ash, and V. Breneman. 2004. "Economic and policy implications of wind-borne entry of Asian soybean rust into the United States." http://www.ers.usda.gov/publications/OCS/APR04/OCS04D02/.

Marchetti, M., J. Melching, and K. Bromfield. 1976. "The Effects of Temperature and Dew Period on Germination and Infection by Uredospores of Phakopsora pachyrhizi." *Journal of Phytopathology* 66:461–463.

NSRL. 1995. "Proceedings of the Soybean Rust Workshop." National Soybean Research Laboratory – J.B. Sinclair and G.L. Hartman, editors.

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

Roberts, M., D. Schimmelpfennig, E. Ashley, and M. Livingston. 2006. "The value of plant disease early-warning systems: A case study of USDA's soybean rust coordianted framework." http://www.ers.usda.gov/publications/err18/err18fm.pdf.

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

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

Tschanz, A., T. Wang, and L. Hu. 1980. "Epidemic Development of Soybean Rust and a Partial Characterization of Resistance to Soybean Rust." *Soybean Rust Newsletter* 3:35–41.

Yeh, C., J. Sinclair, and A. Tschanz. 1982. "Phakopsora pachyrhizi Not Transmitted by Infested Soybean Seeds or Soil." *Soybean Rust Newsletter* 5:44–47.

Tables

Table 1: Loss Scenarios under Fungicide Application

Fungicide (cost)	**Yield Loss**	**(Loss+Cost)***	**Total Loss****
Preventive ($25.63/acre)	1% loss	$31.65/acre	$25,320
Curative ($13.81/acre)	7% loss	$55.81/acre	$44,648
No Application ($0/acre)	25% loss	$150.50/acre	$120,400

* (Revenue Loss + Fungicide Costs).
Assuming an average of 43 bushels per acre and $14.00 per bushel. Fungicide costs are found in Roberts et al (2006).
** Assuming an average farm of 800 acres.

Table 2: Variable Description and Summary Statistics

Variable	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**	**Description**
Zero Infections	1097	14.56517	21.346794	0	386	Inspections with no infections
SBR Research Sites	1051	9.425309	11.523594	0	97	Experimental plots for early detection
E[Net Farm Income] ($1,000)	1095	16.64657	25.442635	-0.43038	237.9526	Expected net farm income
Soy : Other Grains	1097	0.330829	0.2477216	0	1	Ratio of planted soybeans to other grains
Infections	1097	0.99453	3.8990415	0	70	Inspections with an infection
IV Inspections	1097	15.54512	10.387187	0	145.5053	IV estimate of inspections
Nearby Infections	1097	3.250683	8.2334806	0	120	Number of infections in nearby counties
Overwinter Temp/Precip.	1097	0.504137	0.2690798	0.034358	6022.19	Interaction variable: Precipitation during farm season (t-1) x Overwinter temperature.
Overwinter Temp/Humid.	1097	2476.9	1084.38	325.1107	6520	Interaction variable: Humidity during farm season (t-1) x Overwinter temperature.
Overwinter Temp/Wind	1097	29.89339	32.721263	2.652159	330.0878	Interaction variable: Wind speeds during farm season (t-1) x Overwinter temperature.
Soy Harvest:Planted	1097	0.761716	0.403619	0	1	Ratio of harvested to planted soybeans
Soy Plant Date	1097	–	–	–	–	Planting date of soybeans (RMA)
Soy Maturity Group	1097	5.724703	2.5371079	00	8	Maturity group of planted soybeans

Table 3: Two-Stage Bootstrapped Zero-Inflated Poisson Model Results

.... Probit Selection Model				.... Zero-Inflated Poisson Model for Positive Infections			
Parameter	**Estimate**	**Std. Error**	**Elasticity**	**Parameter**	**Estimate**	**Std. Error**	**Elasticity**
Intercept	2.5116***	0.07287		Intercept	2.8599***	0.03892	
Infections, $t-1$	0.3852***	0.06887	0.21097	Infections, $t-1$	0.03027***	0.01044	0.0136
IV Inspections	-0.00988*	0.004278	-0.11274	IV Inspections	0.02384***	0.00202	0.2224
Nearby Infections, $t-1$	-0.00843	0.02504	-0.0153	Nearby Infections, $t-1$	0.007231**	0.002048	0.0107
Overwinter Temp/Precip.	0.0121*	0.003171	0.00447	Overwinter Temp/Precip.	0.294**	0.05722	0.0889
Overwinter Temp/Humid.	-0.00025**	1.60E-05	-0.42559	Overwinter Temp/Humid.	0.000115**	5.78E-06	0.1592
Overwinter Temp/Wind	0.002549	0.08955	0.0559	Overwinter Temp/Wind	0.000286*	2.64E-05	0.0051
Soy Harvested:Planted	0.5815**	0.09672	0.3249	Soy Harvested:Planted	0.4742**	0.04952	0.2166
Soy Plant Date	-0.00013***	2.90E-08	-1.62626	Soy Plant Date	-0.00046***	1.13E-06	-4.6305
Soy Maturity Group	0.04519**	0.02323	0.18976	Soy Maturity Group	0.5505***	0.0622	1.8894

AIC	2,301
SBC	2,391

*** indicates significance at the 1% level
** indicates significance at the 5% level
* indicates significance at the 10% level

Table 4: Two-Stage Bootstrapped Zero-Inflated Negative Binomial Model Results

.... Probit Selection Model				... Zero-Inflated Negative Binomial Model for Positive Infections ...			
Parameter	**Estimate**	**Std. Error**	**Elasticity**	**Parameter**	**Estimate**	**Std. Error**	**Elasticity**
Intercept	-13.4644***	0.1653		Intercept	-13.4589***	0.06047	
Infections$_{t-1}$	0.04074*	0.02439	0.02619	Infections$_{t-1}$	0.06126***	0.01378	0.031
IV Inspections	-0.02015***	0.007064	-0.26991	IV Inspections	0.0183***	0.003201	0.1929
Nearby Infections$_{t-1}$	-0.1394***	0.01708	-0.29712	Nearby Infections$_{t-1}$	0.01655**	0.008361	0.0278
Overwinter Temp/Precip.	-1.1415***	0.261	-0.49551	Overwinter Temp/Precip.	-1.2074***	0.1066	-0.4124
Overwinter Temp/Humid.	0.000337***	0.000052	0.66848	Overwinter Temp/Humid.	0.000329***	0.000024	0.5132
Overwinter Temp/Wind	-0.02564***	0.001648	-0.65989	Overwinter Temp/Wind	0.00835***	0.001973	0.1691
Soy Harvested:Planted$_{t-1}$	0.4795**	0.1908	0.31446	Soy Harvested:Planted$_{t-1}$	0.482***	0.07736	0.2487
Soy Plant Date	0.000565***	9.88E-06	2.16217	Soy Plant Date	0.00058***	3.61E-06	5.1977
Soy Maturity Group	1.0267***	0.02991	2.06083	Soy Maturity Group	0.3822***	0.007842	1.4821
				κ (overdispersion coefficient)	1.5616***	0.147	

AIC	2,233.3
SBC	2,338.3

*** indicates significance at the 1% level
** indicates significance at the 5% level
* indicates significance at the 10% level

Table 5: Two-Stage Block Bootstrapped Zero-Inflated Negative Binomial Model Results

.... Probit Selection Model			... Zero-Inflated Negative Binomial Model for Positive Infections ...		
Parameter	**Estimate**	**Std. Error**	**Parameter**	**Estimate**	**Std. Error**
Intercept	-19.5094***	0.4856	Intercept	-12.8652***	1.0224
Infections, $t-1$	0.084159*	0.04324	Infections, $t-1$	0.0595***	0.01524
IV Inspections	-0.012964***	0.001894	IV Inspections	0.02931***	0.002973
Nearby Infections, $t-1$	-0.06974	0.3252	Nearby Infections, $t-1$	0.005493	0.01503
Overwinter Temp/Precip.	-0.24	0.364	Overwinter Temp/Precip.	1.6934***	0.08058
Overwinter Temp/Humid.	0.000032**	0.00009	Overwinter Temp/Humid.	-0.00047***	0.00002
Overwinter Temp/Wind	-0.02287***	0.005789	Overwinter Temp/Wind	0.02804***	0.001655
Soy Harvested:Planted	0.85703**	0.3254	Soy Harvested:Planted	0.7589***	0.1436
Soy Plant Date	-0.00107	0.000013	Soy Plant Date	0.0004***	2.84E-06
Soy Maturity Group	1.7371***	0.4547	Soy Maturity Group	0.2719***	0.006368
			κ (overdispersion coefficient)	0.482***	0.072

AIC	1,951.5
SBC	2,056.5

*** indicates significance at the 1% level

** indicates significance at the 5% level

* indicates significance at the 10% level

Table 6: Summary Statistics of Estimated Premiums
Rates for Soybean Infections
7% Loss Coverage

	.... Northern U.S. Regions [a]				
	Mean	**Median**	**Std. Dev.**	**Min**	**Max**
Probit	0.0458546	0.0462149	0.0349778	0.0008453	0.1348144
Poisson	0.0538266	0.0493107	0.0408021	0.0038311	0.3476129
Neg. Binomial	0.0518723	0.0530484	0.0334617	0.0054854	0.2658293
ZIP	0.0139829	0.0056599	0.0232818	2.5868E-07	0.2865163
ZINB	0.0159410	0.0094334	0.0258488	1.883E-06	0.3335390
	.... Southern U.S. Regions [b]				
	Mean	**Median**	**Std. Dev.**	**Min**	**Max**
Probit	0.2801540	0.2647688	0.0812436	0.0948213	0.5103642
Poisson	0.3435242	0.3229798	0.0999514	0.1223429	0.5108624
Neg. Binomial	0.2398983	0.2240047	0.0657178	0.1086636	0.4522243
ZIP	0.2838073	0.2588641	0.1125964	0.0498436	0.5056794
ZINB	0.2766790	0.2494677	0.1107381	0.0596603	0.5102695

[a] The Northern U.S. Region contains locations that are north of $36^o39'$ latitude.
[b] The Southern U.S. Region contains locations that are south of $36^o39'$ latitude.

Figures

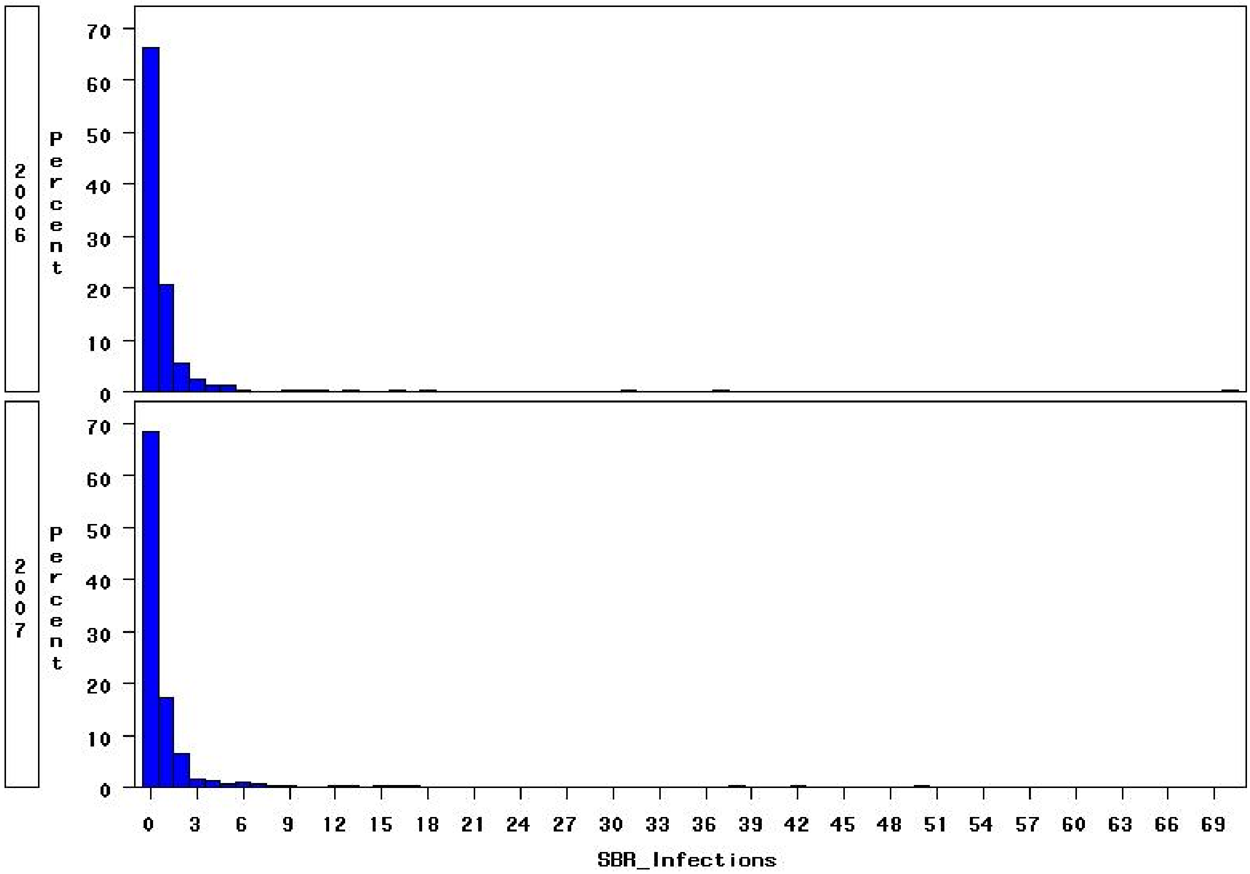

Figure 1: Total Soybean Rust Infections, in percent

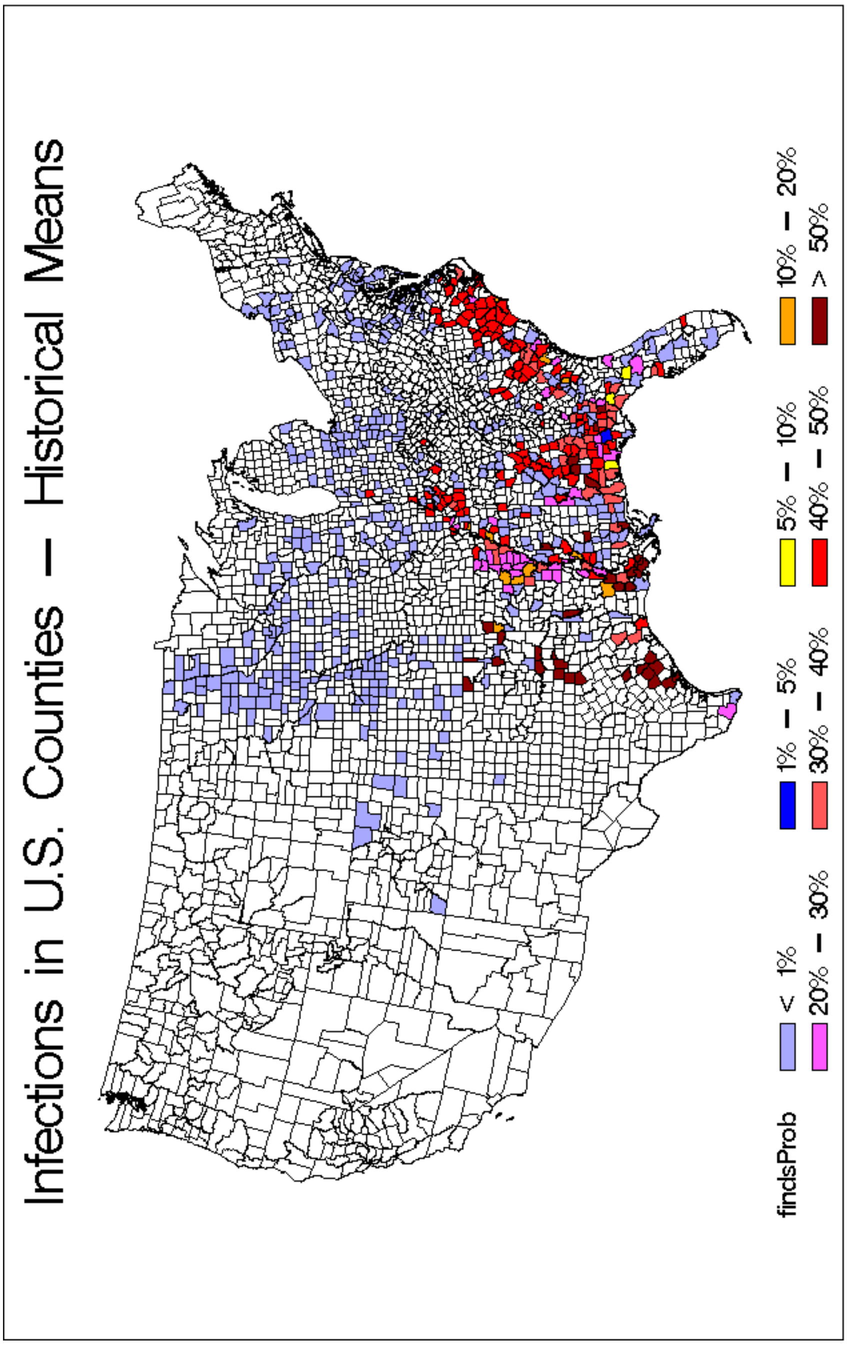

Figure 2: Infection Probabilities using Historical Means

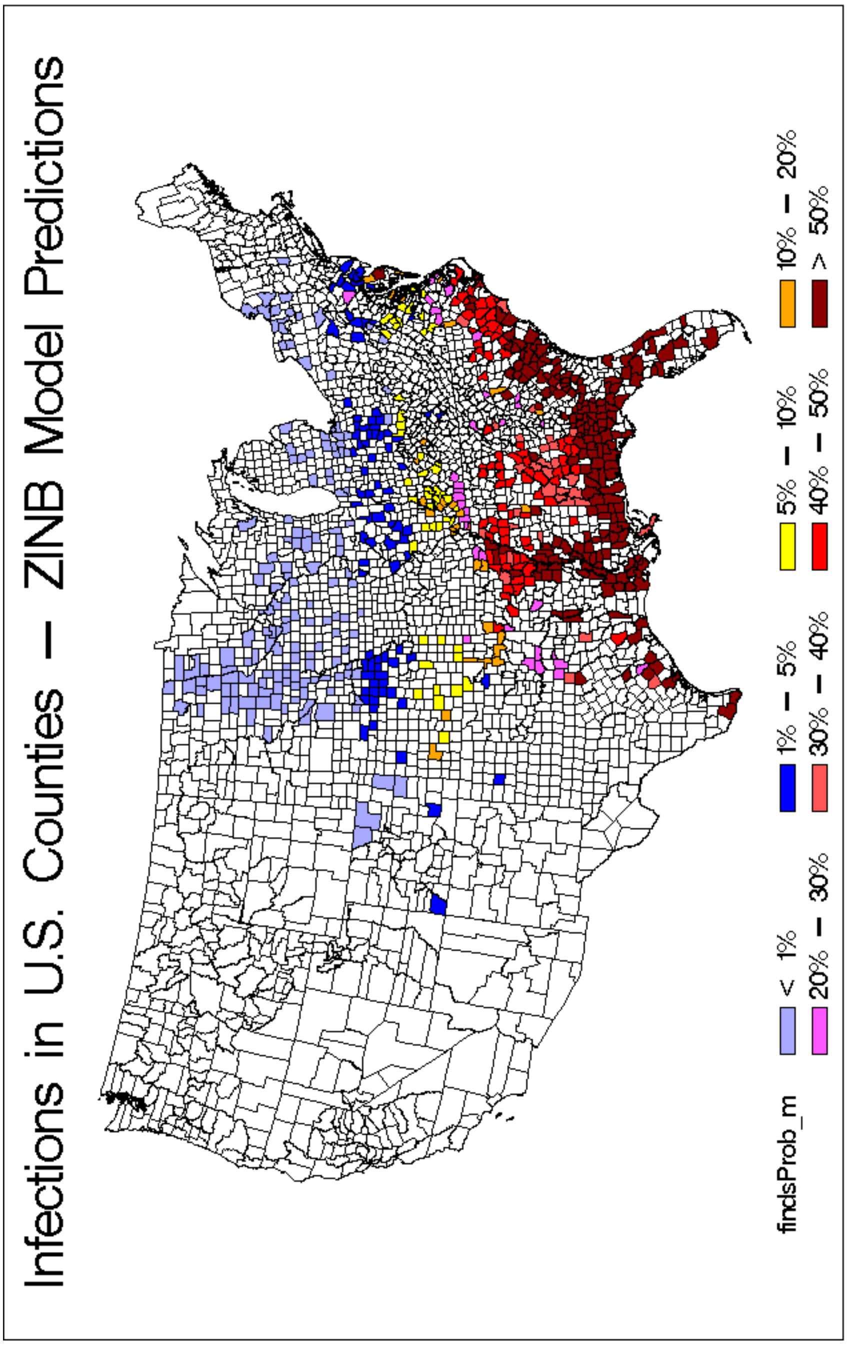

Figure 3: Infection Probabilities Estimated with ZINB Specification