Managing Economic Risk from Invasive Species: Bug Options

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by

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Abstract:

Invasive insect species cause billions of dollars of direct and indirect damage to U.S. crops each year. The market for insuring insect damage is, however, far from complete. The objective of this study is to design and value insect derivatives, or "bug options," which would offer growers a market-based means for transferring risk of pest damage to speculators or others who may profit from higher insect populations. A bug option valuation model is developed and applied to *Bemesia tabaci* infestation in cotton. The results show that insect derivatives may become important risk management tools for a wide range of growers.

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Introduction

Estimates of the economic damage caused by invasive species of all types in the U.S. are alarming high. Moreover, without appropriate policy responses on a macro-level and management techniques on a micro-level, these costs are sure to grow as the U.S. agricultural economy becomes more interrelated with other global players. At one extreme, Pimentel, et al. (2000) estimate the total economic loss to invasive species at $137.0 billion per year. One species alone, the glassywing sharpshooter, which is a vector for Pierce's disease, threatens to destroy the entire $3.3 billion California grape industry (UCANR).[1] Besides the environmental damage cited by Eiswerth and Johnson (2002), invasive species impose both direct and indirect costs on commercial crop production. Direct losses include reductions in yield, lower quality, higher costs of chemical mitigation strategies, and a diversion of management time and attention. Indirect losses, on the other hand, include the government resources used in large-scale eradication programs, quarantines placed on US products by other countries, export sales that are lost outright when importers have alternative sources for the same product, damage to the environment and fragile ecosystems from the potential overuse of pesticides and consumer rejection of products deemed to be "unnatural" because they have been genetically modified or chemically treated to resist pests. Rigorous economic analysis has helped growers mitigate both direct and indirect damage in an efficient way, but the market for pest risk management is far from complete.

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[1] The GWSS also carries strains of xylella fastidiosa that threaten California citrus, alfalfa, almonds, stone fruits and ornamentals – a total of some $27.0 billion in market value (UCANR).

Economic optimization models designed to recommend insecticide application rates and thresholds are typically based on dynamic solution concepts such as maximizing the present value of profit from a given orchard or crop (Regev, Guiterrez and Feder, 1976; Babcock, Lichtenberg and Zilberman, 1992; Hof, 1998; Marsh, Huffaker and Long, 2000; Eiswerth and Johnson; for example). Such models compare the marginal present value of reducing pest damage with the marginal cost of using either biological or chemical control techniques to suggest an optimal solution. This line of research has played an important role in the pest management literature because optimization models allow growers to control specific sources of economic risk in a profit-maximizing way. However, the profit-maximizing level of control is almost certainly not total eradication of the pest, or total elimination of all economic damage.

As a result, even growers who adhere to optimal pest control strategies are still subject to some financial risk. Insurance is not the answer. It is well-known that private insurance markets in agriculture fail for reasons of moral hazard, adverse selection and the high correlation of risks borne by growers. Moreover, government subsidized insurance, particularly for speciality crops, has a history of low participation and excessively high budget costs (Knight and Coble, 1997; Richards and Manfredo, 2003). Many economists emphasize the role of public policy in mitigating the economic damage caused by invasive species (Carter, Chalfant and Goodhue, 2004). Costly government intervention, however, is not the only solution and may, in fact, be less efficient than a market-based one. This study presents a new way growers can mitigate the financial risk from invasive pests by transferring it to others through market-traded instruments known as *insect derivatives*.

Insect derivatives, or "bug options," represent a market-based means for growers to transfer risk to others who may profit from higher insect populations. Derivatives are, in general terms, contracts between two parties specifying a future exchange of money where the amount depends on, or is derived from, the value of an underlying asset or index value. A foreign exchange swap is one example of a financial derivative. In this type of swap, two counterparties agree to exchange an amount of money that depends upon the relative value of two currencies or interest rate swaps, where the amount depends on the difference between a variable rate, such as the London Interbank Offering Rate (LIBOR), and a fixed rate. Weather derivatives are another recent innovation where the amount of money that changes hands is determined by the cumulative value of a temperature index such as cooling-degree days (CDD) relative to an agreed "strike" value that is usually set at an historical, long term average (Richards, Manfredo and Sanders, 2004).

In the case of pest infestations, a grower would enter into a contract – an "insect derivative" – with a chemical company that specifies the payment by the company to the grower should pest populations exceed a certain agreed level. If the population is below the agreed level, then the contract would require the grower to pay the chemical company a similar amount. Both parties have an incentive to sign this contract because the chemical maker would otherwise suffer lower revenues when pest populations are low and the grower would have relatively high pesticide costs when populations rise.[2] In this example, both growers and chemical companies

[2] This is another example of a swap. An option contract would involve the right, but not the obligation, to either buy (call) or sell (put) the underlying index at a fixed value (the strike price). A call option, for example, would rise in value if the index rises above the strike price, while a put option would rise if the index falls. A grower who buys a call option would be protected in the event that the pest population grows.

are effectively managing their net income risk. Although such a derivative seems a natural and logical outgrowth of the normal course of agribusiness, there are several reasons why they have not emerged to this point – reasons that careful academic research such as that proposed herein, can help overcome.

The primary reason bug options do not currently exist is the lack of an agreed pricing mechanism. Therefore, the objective of this study is to develop a risk-neutral valuation method for any species evolving within any well-defined agricultural region.

By creating a relatively straightforward, economically justifiable way of pricing bug options, this research will help ensure that insect derivatives become actively traded between growers and their natural counterparties (chemical companies, insurance companies, nurseries, and many others). Growers, chemical suppliers and consumers in general each have an interest in the outcome of this research. First, growers will be able to plan more effectively, have greater access to lower cost sources of capital, allocate existing capital more effectively, pay lower taxes, on average, due to the fundamental convexity of tax schedules, or avoid the direct and indirect costs of bankruptcy (Smithson, 1998). Second, by trading insect derivatives, chemical companies will have a means of raising capital for new product development, and smoothing the revenue streams that derive from limited-use chemicals. Third, to the extent that growers substitute derivatives for other methods of insect management, active trading in insect derivatives is expected to result in reduced levels of insecticides or other biologically harmful control techniques. Finally, if growers are able to trade instruments that rise in value with the demand for pest control, then they will have an incentive to use the most efficient pest

management techniques available, thereby creating an "in the money" position with respect to the insect derivative.

Developing a pricing model for insect derivatives also represents a significant advance in option valuation. To date, all financial derivatives have been uni-dimensional, meaning that they price claims on financial assets whose benefit flows vary only with time. Our concept of insect derivatives, on the other hand, will be priced in two-dimensions, as the underlying "asset" (the insect population) confers economic damages on growers that vary both through space and time. In this paper, we use recent developments in the fields of environmental economics (pollution control and abatement technologies) and in renewable natural resource management (fish and wildlife populations) to price contingent claims on insect populations that evolve geographically and temporally. We demonstrate the value of this method using field-trial data of *Bemesia tabaci* (whitefly) populations in Arizona and California cotton (Naranjo, Chu and Henneberry, 1996).[3]

The first section of the paper describes the *Bemesia* data used to demonstrate how insect derivatives can be priced. The second section lays out a bioeconometric model of insect population growth, including separate models for both the deterministic part and a stochastic process that forms the core of our pricing model. This section also describes a simple model of cotton yield that incorporates both insect population and control activities. A third section describes the risk-neutral valuation model and the particular assumptions that are made in implementing it with the *Bemisia* example. A final section provides the estimation results and offers some general conclusions for the likelihood of an active insect management program.

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[3] In 1994, Naranjo, et al. report *B. tabaci* was responsible for damaging 345,000 ha of cotton in Arizona and Southern California, reducing total yield by 3.6 million kg.

Empirical Model of Insect Population Growth

Insect Population Data

The data for this study consist of two years of experimental field-trial data on *Bemesia tabaci*

population growth and yield damage gathered by researchers based at the Western Cotton

Research Laboratory (WCRL) in Phoenix, AZ using cotton fields in Brawley, CA (Naranjo, Chu

and Henneberry). Weekly counts of adult *B. tabaci* were collected each year over a 16-week

season for 11 different plots. Plots correspond to various insecticide treatment intensities, from

no applications in a given week to 15 insecticide applications per week. By varying insecticide

treatment levels, we are able to study the impact of frequency and dose on population levels at

different times during the season. Control efforts cause the data to exhibit greater variability than

would otherwise be the case, allowing us to more clearly identify the underlying population

diffusion process. *B. tabaci* is a particularly nefarious pest in the U.S. Southwest as they tend to

travel large distances, reproduce quickly and impair yields significantly by depriving the plant of

vital nutrients. At both locations, yield samples taken at harvest for each plot provide data

regarding the yield-injury relationship in cotton. Table 1 provides a summary of the

experimental insect data.

Bioeconometric Model of Insect Population Growth

Insect populations at a particular location vary from week to week and from year to year.

However, the basic process driving insect counts consists of a deterministic and a stochastic

component. Insect populations are constrained by several biological factors: (1) growth rates

depend on the number of adults available to reproduce, (2) reproduction takes time, (3) the environment has a finite capacity to support insect populations and (4) control activities, typically through insecticides, tend to be quite effective in reducing population counts. Given these facts, entomologists typically model the deterministic part of insect population growth as an exponential function common to virtually all bioeconomic growth models (Clark, 1990; Eiswerth and Johnson):

$$\frac{dB_t^m}{dt} = \alpha_1 B_t^m \left(1 - \frac{B_t^m}{K} \right),$$

(1)

for the mean insect population (B^m) growing at a rate α_1 in an environment with carrying capacity K. The differential equation (1) can be solved for the expected population level at any time, t, which provides a convenient expression for the mean insect population:

$$B_t^m = \left(\frac{K}{1 + de^{-\alpha_1 t}} \right) - g(c_t),$$

(2)

where insecticide applications (c) reduce insect numbers according to the control function g and d represents the starting population value relative to carrying capacity: $(K - B_0)/B_0$. In the empirical application below, g is assumed to be quadratic in order to capture the likely diminishing marginal returns to insecticide application. Depending upon data availability, the mean population may also be a function of temperature, host plant abundance, other non-chemical abatement efforts, or predator population.

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Insect population growth is, however, not entirely deterministic. Random variations from the mean population level are assumed to be governed by a Brownian motion process:

$$dB_t = \mu\, dt + \sigma\, dz, \tag{3}$$

where μ is the drift rate per unit of time, dt, is the standard deviation of the process, and dz is an increment of a standard Weiner process with zero mean and variance equal to dt. As noted by Sunding and Zivin, equation (1) captures several empirical regularities observed across insect groups.[4] Namely, per-period changes in the population as well as the population itself are normally distributed, population levels are always non-negative, and short-run dynamics are dominated by the volatility component whereas long-term dynamics are dominated by trend.

It is not likely, however, that any trend away from the mean in (2) is likely to be sustained over the long-run as insect populations cannot grow without bound, nor is it likely that they disappear without some outside influence. Therefore, the process in (3) is modified to include a mean-reversion term so that:

$$dB_t = \kappa(B_t^m - B_t)dt + \sigma\, dz, \tag{4}$$

where κ is the rate of reversion to the mean. Further, insect populations are also subject to periodic "spikes" or periods of rapid growth driven by environmental factors that are otherwise not accounted for in the model. We model these instances as jumps in the stochastic process

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[4] Note that Sunding and Zivin model population growth as a geometric Brownian motion. However, in our model, the dependence of growth on existing population levels is captured through the mean function (2), so the remaining variation is likely independent of current population levels.

estimated above (Merton, 1976; Jorion, 1989, Naik and Lee, 1990), so the most general form of

the population equation becomes:

$$dB_t = (\kappa(B_t^m - B_t) - \lambda\phi)dt + \sigma dz + \phi dq, \tag{5}$$

where jumps occur according to a Poisson process q with average arrival rate λ and a random

percentage shock, ϕ. The random shock, in turn, is assumed to be log-normally distributed with

mean $\gamma - 0.5\delta^2$ and variance, δ^2. The Poisson process q describes a random variable that assumes

a value of 0 with probability $1 - \lambda$ and 1 with probability λ. Estimates of (5) are obtained by

maximum likelihood estimation over the entire sample data set, using the likelihood function:

$$L(B) = -T\lambda - \frac{T}{2}\ln(2\pi) +$$
$$\sum_{t=1}^{T}\ln\left[\sum_{n=0}^{N}\frac{\lambda^n}{n!}\frac{1}{\sqrt{\sigma + \delta^2 n}}\exp\left(\frac{-(dB_t - (\kappa(B_t^m - B_t) + \sigma/2 + n\delta^2/2 - n\phi))^2}{2(\sigma + \delta^2 n)}\right)\right], \tag{6}$$

where we approximate the change of B_t (dB_t) with a discrete change: $(B_t - B_{t-1})$. Richards,

Manfredo and Sanders (2004) demonstrate this method of estimation using a temperature process

for the Fresno Air Terminal.

    When pricing derivatives on "physical" quantities like insect populations or the weather,

the derivative value depends not only on forecasts of the underlying variable, but on its economic

value to the agents involved in its trade. In the case of insects, traders must be able to estimate

the marginal impact of an increase in insect density on yields and, ultimately, crop revenue. With

experimental data such as that used in the example described below, the USDA entomologists

were careful to ensure that growing conditions among plots were otherwise identical so

differences in yield are solely attributable to variations in insect populations. Yield is expected

to be concave in both insect population and control activities, so we specify yield as a simple

quadratic function of both:

$$y_t = \beta_0 + \beta_1 B_t + \beta_2 B_t^2 + \beta_3 c_t + \beta_4 c_t^2 + \beta_5 D94 + \epsilon_t, \tag{7}$$

where D94 is a binary variable for the year 1994 ($D94 = 1$), ϵ_t is an iid random error vector and

the remaining variables are as described above. Because we do not have data on other inputs, all

of explanatory variables are either exogenous or determined by the researcher, so ordinary least

squares provides consistent estimates of all parameters. Marginal revenue impacts are calculated

by multiplying the derivative of yield with respect to insect population by an expected output

price, which is assumed to be the long-term average market price in the application described

below.

Pricing Insect Derivatives

An insect derivative is a contingent security based on the value of an underlying insect

population index. If the derivative is specifically an option, then it will have a positive intrinsic

value if the actual realized population is higher (lower) than the agreed strike level for a call (put)

option. By buying an insect call option, a grower may be able to effectively protect himself or

herself from financial loss should an insect population rise above the strike level. There are five

essential elements that form any insect derivative: (1) the underlying insect population index, (2)

the length of time of the contract prior to expiration, (3) the location for where the underlying

insect population is reported (e.g., farm, orchard, experiment station or larger aggregation of

farms), (4) the dollar value attached to each unit of the underlying index (marginal loss in revenue attributable to an additional insect), and (5) the strike population index value. At the agreed expiration date of the option, a holder of a call option will receive payment if the insect population index is greater than the strike price, and the holder of a put option will receive payment if the insect population index is less than the strike price. The amount of payment is equal to the level of insect populations that are greater (less) than the strike price multiplied by some notional value dollar value per unit of the underlying insect population index. In the case where the option is not exercised, the option buyer will forfeit his option premium. Sellers of options, or option writers, receive a premium for providing this option to the option buyer.

As explain in the introduction, the proper pricing of such an instrument is critical for its successful trade. Indeed, if these derivatives are mispriced in the market place, traders will not be attracted to the contract and leading to liquidity problems. As well, there is likely to be abnormally large bid-ask spreads that could hamper liquidity of the market. While insect derivatives are likely only to be traded only over-the-counter, it is still critical that appropriate pricing models be used. If the insect population represents a hedgeable risk, or one that growers can transfer by trading an underlying futures contract, then it would be possible to price an insect option using a traditional, no-arbitrage, Black-Scholes pricing model. However, as in the case of weather derivatives (Richards, Manfredo and Sanders), insect populations are not tradable assets. Without an effective hedge, we must consider the role of the market price of risk and devise a way of estimating its impact on derivative prices.

Fortunately, because insect populations are not likely to be correlated with the market portfolio, we can use the risk-neutral valuation model of Cox, Ingersoll and Ross (1985) and

proceed by following a three-stage algorithm. First, we "risk neutralize" the insect population

process by estimating the process defined in (5) and removing all dynamics that are explainable

by changes in the mean, by mean reversion or by jump processes. The remaining random

variation is then a martingale, Q, and dz becomes dv, where v_t is a Q-Weiner process (Alaton, et

al.). Second, we form an expectation of the intrinsic value of the derivative under the Q measure

defined by our risk-neutralized process. Third, we discount the expected payoff value back to the

current date at the risk-free rate. This discounted expected payoff is the market equilibrium price

of the derivative. More formally, given a constant market price of risk, a constant rate of interest,

r, and assuming each contract pays one dollar per unit of insect population, the martingale that

defines the underlying index becomes:

$$dB_t = (dB_t^m/dt + \tau(B^{m_t} - B^m) - \lambda\phi - (\delta + \psi)\sigma)dt + \sigma dv + \phi dq, \qquad (8)$$

where dv is now a Q-Wiener process (Alaton, et al) and ψ is the market price of risk. Hull

(2002), however, argues that if the underlying is indeed statistically independent of the market

portfolio, then the market price of risk is zero. Because this is likely to be case for localized

insect populations, we set $\psi = 0$ in (8) and proceed to price the derivative using the risk free

discount rate.

To demonstrate the third step of the pricing algorithm, we consider the specific case of a

call option. The expected payoff to a call option is given by: $C_T = \max [B_T - \bar{X}, 0]$, where $\bar{X}$

is the strike population value. This expectation must be found under Q-measure. Taking the

expectation and discounting to the present from T at the rate r gives a call-option value of:

$$c_t = e^{-r(T-t)}\left[(\mu_n - \bar{X})\Phi(B_t) + \frac{\sigma_n}{\sqrt{2\pi}}e^{\frac{-\sigma^2}{n}} \right], \qquad (9)$$

where μ_n and σ_n are the mean and variance, respectively, of the insect process and Φ is the

standard normal distribution function.[5] The value of a put option, or any other derivative where

the payoff can be similarly defined, can be found the same way. With these prices, therefore,

traders in the market can be fully confident that the market price reflects full economic value to

both buyers and sellers – or that they are equivalent to an "actuarially sound" premium in

insurance terminology.

Results and Discussion

Recall that the objective of this study is to design an insect derivative and to develop and

implement a model that can be used to arrive at a market value for any variation of the

instrument we create. Because this objective involves several steps, our discussion of the results

considers each in turn: (1) estimates of the deterministic insect population function, (2) estimates

of the stochastic process that drives variation from the mean, (3) estimates of the impact of

Bemesia tabaci on cotton yields, and (4) estimates of an example insect derivative, herein

defined as a call option on *Bemesia tabaci* at the Brawley, CA research station.

Table 2 presents estimates of the deterministic part of the insect growth model. In this

model, carrying capacity is allowed to vary from one year to the next because we cannot

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[5] The mean and variance found under Q-measure include the market price of risk and jump terms, but their
specific form are not material here. They have been derived, however, and are available from the authors.

otherwise control for the temperature, the amount of vegetation or other factors that may influence the maximum supportable population. However, the results in table 2 show that the maximum supportable population in 1993 was 19.639 insects per cm^2, but the maximum population in 1994 does not differ significantly. The rate of growth was also initially allowed to differ between the two years but, perhaps due to the relatively small number of time-series observations available for each plot, the estimation procedure could not identify two separate growth rates. Therefore, we maintain an assumption throughout that the rate of population growth in both years averages approximately 12.6% per week. Next, estimates of the control function suggest that insecticide applications were subject to diminishing marginal returns each year. However, insecticide appears to have been significantly more effective during 1994, where the marginal effect (evaluated at sample means) was 1.081 fewer insects per application, versus 0.901 fewer in 1993. Finally, for reasons of either weather, lack of predators or some other factor that we could not measure, the average population in 1994 was fully 30.8 more insects per leaf than in 1993.

[table 2 in here]

After removing the deterministic mean from the observed insect series, we then estimated three alternative stochastic processes in an attempt to explain the remaining, random variation. Starting with the simplest, most parsimonious model, we estimated: (1) a simple Brownian motion (BM), (2) a Brownian motion with mean-reversion (BM-MR), and (3) a mean-reverting Brownian motion with discrete, Poisson-distributed jumps (BM-MR-J). Table 3 shows the parameters from each model and the results from testing among the competing models. Because each is nested within the more complicated alternative, likelihood ratio (LR) tests suffice for

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model selection. For the first comparison (BM verus BM-MR), the resulting LR statistic is chi-square distributed with 1 degree of freedom. At a 5% level, the critical chi-square value is 3.84, while the test statistic value is 197.84, so we clearly reject the BM model in favor of the BM-MR. Second, the LR test statistic used to compare the BM-MR and BM-MR-J models has a critical value of 7.82 while the estimated LR chi-square value is 26.58, again suggesting rejection of the more parsimonious model. Based on these results, therefore, we expect a drift rate away from the underlying trend of approximately 1 insect per leaf per week. Deviations from trend tend to return to the mean at a rate of 37.0% per week. Further, we expect to observe jumps in insect numbers of 43.45 insects per week approximately 20% of the time. Clearly, jumps this large and frequent are a dominant characteristic of the process driving *Bemesia* growth, so will be a major factor in pricing any derivative written for them.

[table 3 in here]

Because the BM-MR-J model was found to dominate the others, we use this model to form expectations of *Bemisia* numbers at contract expiry. In order to assign an economic value to each population level, however, it is first necessary to estimate the marginal impact of an infestation on cotton yields. The yield model results are shown in table 4 below. Based on sample average population values, the marginal effect of an additional adult *Bemisia* throughout the growing season is a loss of 4.656 kg / ha. Using the long-term average price for cotton of $1.32 / kg, this implies that each additional adult costs cotton growers approximately $6.03 per ha. We use this value to determine the price of an option to transfer the implied economic risk to a third party. Notice also from this table that growers can reduce the damage from any given

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population level by spraying insecticide, but their ability to do so is subject to sharply diminishing marginal returns.

[table 4 in here]

Finally, table 5 provides estimates of the price of a call option written on *Bemisia* numbers at the Brawley experiment station. Because the strike price is a significant element of the option contract that is subject to negotiation between both parties, we provide option value estimates for a range of strike-population levels. Given that the average population value over the sample period is 8.72 adults per leaf, we expect that all concentrations above this value will generate a positive call option value. Further, the higher the strike price, the less financial "insurance" insect options provide their holder. As a result, we expect lower option values the higher the strike price. The results in table 5 show this to be the case. Specifically, if a grower expects significant economic damage if insect counts rise above 20 adults per leaf, then buying a call option for protection at any realized population above this level will cost $86,051. Because this price is fully justifiable on economic grounds, both the grower and counterparty (eg. an insecticide company) will agree to this price and will enter the option contract willingly.

Conclusions and Implications

In this study, we have shown that it is possible to design a financial instrument that could allow growers to transfer the financial risk of insect damage to their crop. Further, because data on insect populations are readily available through pheremone traps or through rigorous scientific experimentation, it is possible to value derivative contracts written for a specific crop and location. More importantly, perhaps, because insect numbers are independent of financial

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markets or other measures of broader economic performance, risk neutral valuation methods are relatively simple and easy to use.

Although we have shown that it is possible to design and price an insect derivative, future research in this area should investigate issues of basis risk – or how an individual grower's exposure differs from that measured at an experiment station or other monitoring point – and how this can impact his or her risk management strategy with insect derivatives. In particular, our valuation method addresses issues of spatial population variation only in an implicit way, namely by estimating the population process at a specific place. However, future research should work to incorporate stochastic processes in the spatial dimension as well. Second, more research should be conducted using other insect species in order to determine whether the growth processes estimated here are typical of insects in general, or if *Bemesia* represent somewhat of an anomaly. Third, before insect derivatives become widespread, there is still much work to be done in designing institutions and markets that can facilitate their trade. While weather derivatives are still in their infancy, interest from energy firms and others in the trading industry has lead to the development of a significant pool of interest in their trade. Building similar interest is necessary to bring insect derivatives from theoretical possibility to a tradable reality.

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Table 1. Summary of *Bemesia tabaci* Trial Data: Brawley, CA, 1993 - 1994.

	N	Mean	Std. Dev.	Min.	Max.
Random Parameter Values					
Treatments (# per week)	358	8.637	4.174	0.000	15.000
Eggs (#/cm^2)	358	7.640	19.879	0.000	136.280
Nymphs (#/cm^2)	358	1.814	4.546	0.000	34.180
Adults (#/leaf)	358	8.720	17.933	0.000	128.050
Yield (kg/ha)	358	1,515.094	377.683	601.750	2,007.250

Fixed Parameter Values					
Risk Free Rate	3.0%				
Cotton Price ($/kg)	1.32				
Days to Expiry	105				

Table 2. Insect Population Mean Function Estimates: MLE

Parameter	Estimate	t-ratio
$K_{0,1993}$	19.639*	6.454
$K_{0,1994}$	21.811	0.529
α	0.126*	11.633
g_{11}	2.277*	3.017
g_{12}	5.417*	4.230
g_{21}	-0.086	-1.714
g_{22}	-0.271*	-3.226
1994	30.792*	7.292
LLF	-1,375.011	
χ_2	1,694.820	

[a] In this table, the parameters are defined as follows: $K_{0,t}$ is the carrying capacity of the environment in year t, α is the rate of growth, g_{nm} is the linear (m = 1) or quadratic (m = 2) control parameter in 1993 (n = 1) or 1994 (n = 2), and 1994 is a binary variable for the trials conducted in 1994. The χ^2 statistic compares the estimated log-likelihood function model to a null alterative and has a critical value of 15.51 with eight degrees of freedom at a 5% level of significance. For all parameters, a single asterisk indicates significance at a 5% level.

Table 3. Insect Stochastic Process Model Estimates: MLE

Model #1: Brownian Motion (BM)[a]			Model #2: BM with Mean Reversion (BM-MR)			Model #3: BM-MR with Jumps (BM-MR-J)		
Parameter	Estimate	t-ratio	Parameter	Estimate	t-ratio	Parameter	Estimate	t-ratio
σ_1	255.882*	12.991	σ_2	141.762*	13.163	σ_3	96.161*	11.746
μ_1	1.182	1.359	μ_2	1.031	1.704	μ_3	1.032*	3.961
			κ_2	0.728*	16.445	κ_3	0.370*	6.183
						λ_3	0.193*	6.524
						δ_3	28.143	1.511
						ϕ_3	43.451*	8.455
LLF	-1404.08			-1305.16			-1291.87	

[a] In this table, a single asterisk indicates significance at a 5% level.

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Table 4. Cotton Yield Model: OLS

Parameter	Estimate	t-ratio
Constant	464.931	5.092
B_t	-5.333	-4.391
B_t^2	0.048	3.053
X_t	197.252	1.943
X_t^2	-7.551	-5.292
1994	290.745	6.721
R^2	0.863	

Table 5. Insect Derivative Price Estimates

Strike Population	Call Option Value - Vc	Standard Deviation
20	$86,051.00	$12,934.00
25	$79,562.00	$11,619.00
30	$66,461.00	$11,811.00
35	$57,076.00	$11,686.00
40	$47,472.00	$11,513.00