
Managing Economic Risk Caused by Insects: Bug Options

Timothy J. Richards, James Eaves, Valerie Fournier, S. E. Naranjo, C.-C. Chu, and T. J. Henneberry

Abstract

The market for insuring insect damage is far from complete. This study introduces a new type of derivative instrument—insect derivatives—that provide growers a market-based means of transferring insect risk to speculators or others who may profit from higher insect populations. A risk-neutral valuation model is developed and applied to *Bemisia tabaci* population data. Economic simulation models show how insect derivatives can improve risk-return results for a representative cotton farm in the Imperial Valley of California. The results suggest that insect derivatives may become important risk management tools for a wide range of growers.

Key words: *Bemisia tabaci*, cotton, derivatives, forecasting models, insects, insurance, risk management

Estimates of the economic damage caused by invasive species of all types in the United States are alarmingly high. Pimentel et al. (2000) estimate the total economic loss to invasive species at \$137 billion per year. Although insects form only part of the larger invasive species problem, they hold perhaps the most potential for significant economic damage. Indeed, consider the example of the glassy-winged sharpshooter (a vector or carrier for Pierce's disease). If left unchecked, many believe this one species would likely destroy the entire \$3.3 billion California grape industry [University of California Agricultural and Natural Resources (UCANR), 2004].¹

Beyond the direct impacts on yield and quality due to feeding and reproduction, the indirect costs of insect infestation include widespread ecological damage due to chemical control activities, the budgetary cost of government eradication efforts, and the loss of important export markets, to name a few. While current chemical and biological control methods are becoming increasingly effective in managing pest outbreaks, they are costly. In fact, the total amount spent in the United States on agricultural insecticides in 2001 was approximately \$1.326 billion (Kiely, Donaldson, and Grube, 2004). Clearly, growers need a method of controlling not only the agronomic risk from insect

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¹ The glassy-winged sharpshooter also carries strains of *Xylella fastidiosa* that threaten California citrus, alfalfa, almonds, stone fruits, and ornamentals—a total of some \$27 billion in market value (UCANR, 2004).

infestations, but the economic risk as well.²

In the past, economists created dynamic optimization models intended to produce recommendations for insecticide application rates and thresholds. Typically, these models maximize the present value of profit from a given orchard or crop by choosing an insecticide application rate based on thresholds estimated from insect population growth and yield damage functions (e.g., Regev, Guitierrez, and Feder, 1976; Babcock, Lichtenberg, and Zilberman, 1992; Hof, 1998; Marsh, Huffaker, and Long, 2000; Eiswerth and Johnson, 2002).

An optimal solution equates the marginal present value of reducing pest damage with the marginal cost of using either biological or chemical control techniques. 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 loss in a profit-maximizing way. However, economic optimization does not imply the elimination of risk, or the *variability* of profit. Even if a grower were to follow an optimal control program, the cost of insect management will vary from season to season depending on the realization of actual insect densities and a variety of other environmental factors.

Growers have limited access to insurance products that would otherwise allow them to manage economic risk. Indeed, the market for pest risk management is far from complete. 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-

²The importance of invasive species in general is indicated by the amount of research activity on this topic. In fact, as this paper was going to press, a special issue of the *Agricultural and Resource Economics Review* 35(April 2006) was dedicated to the economics of invasive species.

subsidized insurance, particularly for speciality crops, has a history of low participation and excessively high budget costs (Knight and Coble, 1997; Richards and Manfredi, 2003). Many economists emphasize the role of public policy in mitigating the economic damage caused by insects (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 approach growers can use to 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 swap is perhaps the simplest example of a derivative. To create an insect swap, a grower would enter into a contract (the insect derivative) with a counterparty that specifies how much it will pay to the grower should a specific pest population exceed a certain agreed level.³ If the population is below the agreed level, then the contract would require payment by the grower to the counterparty. Both parties have an incentive to sign this contract because the counterparty would presumably suffer lower revenues when pest populations are low and the grower would have relatively high pesticide costs

³Clearly, the "agreed level" would be one that is not actively managed by the grower. Counterparties would agree to an objective measurement standard such as traps at the nearest experiment station, or another, orchard-specific sanctuary. If the grower is paid for higher insect counts, then there is no incentive for fraud. Note that this example assumes growers spray only when insect populations are realized, and not as a matter of course at the start of a growing season. This assumption is consistent with current integrated pest management practice.

when populations rise.⁴ In this example, both growers and counterparties are effectively managing their net income risk.

Although such derivatives seem a natural and logical outgrowth of the normal course of agribusiness, there are several reasons why they have not emerged to this point—reasons which careful academic research, such as that developed in this study, can help overcome. Specifically, the primary reason bug options have not yet gained acceptance is the lack of an agreed pricing mechanism. Therefore, the objective of this analysis is to develop a simple and intuitive 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 seeks to ensure that insect derivatives become actively traded between growers and their natural counterparties (chemical companies, insurance companies, insectaries, 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 be able to smooth revenue streams from limited-use chemicals, thus increasing the likelihood that any risk-sensitive capital budgeting analysis will recommend their development. Third, to the extent that growers substitute derivatives for other methods of insect management, active

⁴ In the application below, we consider insect options. 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 the pest population grows.

trading in insect derivatives can result in reduced levels of insecticides or other biologically harmful control techniques.⁵ Finally, if growers are able to trade instruments which 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.

Our pricing model relies on recent developments in the theory of “risk-neutral” pricing of derivative securities. Whereas financial options—options on stocks or commodity futures—are commonly priced using models derived from sophisticated arbitrage arguments, there are no complementary securities upon which to base similar methods in the case of insect derivatives. In the absence of such riskless hedging opportunities, it is often the case that analysts must resort to equilibrium pricing models that take into account the market price of risk, or the risk premium required by investors in order to purchase a security which is likely to add to the overall riskiness of their portfolio (Cao and Wei, 1999; Richards, Manfreda, and Sanders, 2004).

However, if insect population growth is independent of the returns to a broad market portfolio of other securities, then we can use a risk-neutral approach (Cox, Ingersoll, and Ross, 1985), which does not require an estimate of the market price of

⁵ Note that if chemical insecticides are priced competitively, growers should be indifferent between spraying and not spraying. Growers can either let insect populations grow unabated and accept payment on the derivative to offset real damage, or spray to control insect population growth and use the derivative payment to offset chemical costs. In the former case, derivatives and chemicals are substitutes, whereas in the latter they are complements. Using insect derivatives to reduce insecticide cost is similar to growers who may use rainfall derivatives to offset irrigation costs (Turvey, 1999). It is reasonable to assume, although substitution remains a possibility, most growers will use chemicals, or other integrated pest management (IPM) methods as part of a program of good farming practices, and use insect derivatives to offset the cost of doing so.

risk. Risk-neutral valuation involves finding the expected value of the population level at the agreed termination date of the derivative, comparing the expected value to an agreed "strike" or trigger population level, and discounting the difference (multiplied by a notional dollar figure) back to the contract date at the risk-free interest rate.

When the market price of risk does not enter the calculation, risk-neutral valuation is similar to the method used by insurance companies to determine insurance premia, or actuarial pricing (Hull, 2005). We demonstrate the simplicity of this method using two years of field-trial data of *Bemisia tabaci* (*Homoptera: Aleyrodidae*, also known as whitefly) populations in California cotton (Naranjo, Chu, and Henneberry, 1996).⁶ After arriving at a price series for a family of derivatives at different strike population levels, a stochastic *pro forma* financial statement simulation model is used to demonstrate the effectiveness of insect derivatives in mitigating the financial risk caused by insect infestation.

The remainder of the paper is organized as follows. The first section describes the pest insect *B. tabaci* data. In the second section, we derive a bioeconometric model of insect population growth, including separate components for the stochastic and deterministic elements of population growth—or the random and nonrandom parts, respectively. 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 made in implementing it with the *B. tabaci* example. The fourth section provides an explanation of how we evaluate the effectiveness of insect derivatives in mitigating financial risk, including a

description of a simple stochastic simulation model and the associated measures of risk exposure. A final section provides the estimation and simulation results and offers some general conclusions for the likely value of an insect derivative-based risk management program.

Empirical Model of Insect Population Growth

Insect Population Data

The data for this study consist of two years of experimental field-trial data on *B. tabaci* population growth and yield damage gathered by researchers based at the Western Cotton Research Laboratory (WCRL) in Phoenix, Arizona, using cotton fields in Brawley, California (Naranjo, Chu, and Henneberry, 1996; Naranjo et al., 1998). 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, the field-trial data provide information on 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, which more clearly identifies 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. Yield samples taken at harvest for each plot provide data regarding the yield-injury relationship in cotton. Table 1 gives a summary of the experimental insect data.

Data for the risk management simulation model are taken from a representative Imperial County cotton farm budget prepared by University of California Cooperative Extension officials (University of California, 2005).

⁶Naranjo, Chu, and Henneberry (1996) report *B. tabaci* was responsible in 1994 for damaging 345,000 ha of cotton in Arizona and southern California, reducing total yield by 3.6 million kg.

Table 1. Summary of Bemisia tabaci Trial Data: Brawley, CA (1993–1994)

Description	N	Mean	Std. Dev.	Minimum	Maximum
Random Parameters:					
Treatments (no./week)	358	8.637	4.174	0.000	15.000
Eggs (no./cm ²)	358	7.640	19.879	0.000	136.280
Nymphs (no./cm ²)	358	1.814	4.546	0.000	34.180
Adults (no./leaf)	358	30.637	32.028	3.314	128.050
Yield (kg/ha)	25	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				

Operating costs reflect all land preparation, seeding, growing, and harvesting costs, and are expressed in current, 2004 values. Growing costs include the material and labor costs for a number of insect treatments equal to the sample average from the *B. tabaci* trial data. Revenues, on the other hand, are calculated using 2004 harvest prices obtained from the USDA's Economic Research Service (2005).

Bioeconometric Model of Insect Population Growth

Insect populations at a particular location vary from week to week and from year to year. While some of the observed population growth within a season is predictable, there is a significant random component. In other words, the basic process driving the number of insects at one location consists of a deterministic and a stochastic component. Therefore, we follow the approach taken by Alaton, Djehiche, and Stillberger (2002) in their modeling of weather processes, and first remove the deterministic mean part of insect population growth before modeling random variations about the mean.

Insect populations are constrained by several biological factors: (a) growth rates depend on the number of adults available to reproduce; (b) reproduction takes time; (c) the environment has a finite capacity to

support insect populations; and (d) control activities, typically through insecticides, tend to be quite effective in reducing population counts. Given these facts, the deterministic part of insect population growth can be modeled as an exponential function common to many other types of bioeconomic growth processes (Clark, 1990; Eiswerth and Johnson, 2002):

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

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 (see the Appendix), which provides a convenient expression for the mean insect population:

$$(2) \quad B_t^m = \left(\frac{K}{1 + de^{-\alpha_1 t}} \right) - g(c_t),$$

where insecticide applications (c) reduce insect numbers according to the control function g , and d represents the starting population value (B_0) 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. Entomological research finds that mean population may also be a function of temperature, host plant abundance, other non-chemical

abatement efforts, or natural enemy population (Elswerth and Johnson, 2002).⁷

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

$$(3) \quad dB_t = \mu dt + \sigma dz,$$

where μ is the drift rate per unit of time (dt), σ is the standard deviation of the process, and dz is an increment of a standard Wiener process with zero mean and variance equal to dt .⁸ As noted by Sunding and Zivin (2000), equation (1) captures several empirical regularities observed across insect groups.⁹ Specifically, per period changes in the population as well as the population itself are normally distributed, population levels are always nonnegative, 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) would 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 whereby:

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

⁷ In the empirical application described below, neither daily temperature nor precipitation were significant determinants of insect population levels. Data on other factors were not available. Estimation and hypothesis testing results of the growth models that included weather variables are available from the authors upon request.

⁸ The drift term μ is the drift in the stochastic process away from the mean function described in (1). Therefore, it is fundamentally different from the natural growth rate (α) of the mean data-generating process.

⁹ Sunding and Zivin (2000) 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.

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 otherwise not accounted for in the model. We model these instances as jumps in the stochastic process estimated above (Merton, 1976; Jorion, 1989; Naik and Lee, 1990), so the most general form of the population equation becomes:

$$(5) \quad dB_t = \left(\kappa(B_t^m - B_t) - \lambda\phi \right) dt + \sigma dz + \phi dq,$$

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 lognormally distributed with mean $\phi - 0.5\delta^2$, and variance δ^2 . The Poisson process q describes a random variable that assumes a value of zero with probability $1 - \lambda$, and a value of one with probability λ .

Estimates of (5) are obtained by maximum-likelihood estimation over the entire sample data set, using the likelihood function:

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

where T is the total number of time-series observations, and N is defined as a number of jumps sufficiently large to include all potential jumps in the observed data (six proved sufficient in this application). Further, we approximate the change of B_t (dB_t) with a discrete change: $(B_t - B_{t-1})$. Richards, Manfredo, and Sanders (2004) demonstrate how this method can be used to estimate a similar type of process in an application to derivatives based on temperature indices (weather derivatives).

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 than the agreed strike level for a call option, or, conversely, lower for a 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: (a) the underlying insect population index; (b) the length of time of the contract prior to expiration; (c) the location for where the underlying insect population is reported (e.g., farm, orchard, experiment station, or larger aggregation of farms); (d) the dollar value attached to each unit of the underlying index (marginal loss in revenue attributable to an additional insect); and (e) 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 population that is greater (less) than the strike price multiplied by some notional 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 or her option premium. Sellers of options, or option writers, receive a premium for providing this option to the option buyer.

As explained in the introduction, the proper pricing of such an instrument is critical for its successful trade. Indeed, if these derivatives are mispriced in the marketplace, traders will not be attracted to the contract, leading to liquidity problems. In addition, large bid-ask spreads in the absence of a commonly

agreed pricing model could also hamper market liquidity. While insect derivatives are likely to be traded only over the counter, it is still critical that appropriate pricing models be used.

There are essentially three ways to price insect derivatives. First, "burn rate" or actuarial models use historical probabilities to form estimates of expected payout values at some time in the future. Discounting the expected payout to the present represents an "actuarially fair" derivative price. Although simple to use, burn rate models do not take into account the complex nature of insect growth processes, nor is there any way to update population estimates as the season progresses. Consequently, derivatives priced this way will trade infrequently, if at all (Dischel, 1998; Pirrong and Jermakyan, 1999; Zeng, 2000).

Second, if insects could be hedged, then it would be possible to price insect options using a traditional, no-arbitrage, Black-Scholes pricing model (Black, 1976). However, as in the case of weather derivatives (Richards, Manfredo, and Sanders, 2004), 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.

A third method for pricing insect derivatives provides a more viable alternative. 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.¹⁰ First, we "risk neutralize" the insect population

¹⁰Turvey (2005) uses a similar argument to price degree-day weather derivatives. Yet, in the case of weather, it is less obvious that weather is uncorrelated with the market portfolio. Can and Wei (1999) provide evidence to the contrary, as do Richards, Manfredo, and Sanders (2004). Turvey contends, however, that this finding is immaterial if traders are able to diversify weather risk across several local markets. If this is the case, then the "weather beta" will be zero and a risk-neutral approach can be used.

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 \mathcal{Q} , and dz becomes dv , where v_t is a \mathcal{Q} -Weiner process (Alaton, Djehiche, and Stillberger, 2002). Second, we form an expectation of the intrinsic value of the derivative under the \mathcal{Q} -measure defined by our risk-neutralized process. Third, the expected payoff value is discounted back to the current date at the risk-free rate. This discounted expected payoff is the market equilibrium price of the derivative.¹¹

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:

$$(7) \quad dB_t = \left(\frac{dB_t^m}{dt} + \tau(B^{m_t} - B^m) - \lambda\phi - (\delta + \psi)\sigma \right) dt + \sigma dv + \phi dq,$$

where dv is now a \mathcal{Q} -Wiener process (Alaton, Djehiche, and Stillberger, 2002), and ψ is the market price of risk. As argued by Hull (2005), however, 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 the case for localized insect populations, we set $\psi = 0$ in (7) 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

¹¹ Although risk-neutral valuation is typically applied in cases where the underlying is lognormally distributed, it is only required that the adjusted probability distribution under which the expectation is taken be the one which is consistent with the underlying following a martingale (zero drift stochastic process) (Harrison and Kreps, 1979). For a recent application of this approach, and a review of whether or not the martingale restriction holds in practice, see Turvey and Komar (2006).

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 the \mathcal{Q} -measure. Taking the expectation and discounting to the present from T at the rate r gives a call-option value of:

$$(8) \quad V_c = e^{-r(T-t)} \times \left((\mu_n - \bar{X})\Phi(B_t) + \frac{\sigma_n}{\sqrt{2\pi}} e^{-\sigma^2/n} \right),$$

where μ_n and σ_n are the mean and variance, respectively, of the insect process, and Φ is the standard normal distribution function.¹²

The expectation in (8) is found numerically using a Monte Carlo simulation with 100 random draws of the continuous diffusion process and 100 independent draws of the discrete Poisson jump process (for a total of 10,000 random combinations). Multiplying the expected insect population value that lies below the strike population value by a notional \$1 "tick rate" and finding the present value yields an estimate of the value of a hypothetical call option. 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 price reflects full economic value to both buyers and sellers—or, in insurance terminology, that they are equivalent to an "actuarially sound" premium.

Simulating Risk Mitigation with Insect Derivatives

When pricing derivatives on "physical" quantities like insect populations or the weather, derivative prices depend only on

¹²The mean and variance found under the \mathcal{Q} -measure include the market price of risk and jump terms, but their specific forms are not material here. They have been derived, however, and are available from the authors upon request.

forecasts of the underlying variable and interest rates, but their economic value to any particular grower depends on a number of other variables. Specifically, economic value is defined in terms of the utility created for a representative grower by the opportunity to use insect derivatives to reduce the variability of net income.

Utility rises in the level of net income, but at a declining rate (declining marginal utility of income). The rate at which marginal utility declines as net income increases is determined by the degree of risk aversion of the representative grower, γ .¹³ Higher values of γ suggest a more rapid rate of diminishing marginal utility of income, and hence a greater degree of risk aversion.

Formally, define a power utility function where $U_g(\pi)$ represents the utility of a representative grower g from earning an uncertain level of profit π_g , and γ is the coefficient of risk aversion such that:

$$(9) \quad E[U_g(\pi)] = E\left[\frac{\pi_g^{1-\gamma}}{1-\gamma}\right],$$

where $0 < \gamma < 1$ for concavity and $E[\cdot]$ is the expectation operator. Power utility is an attractive alternative because it is a simple representation that possesses all the characteristics required of a well-behaved utility function: it is concave by construction, it implies a constant relative risk-aversion level (γ) and in profit provided $0 < \gamma < 1$, and decreasing absolute risk aversion as wealth rises. If $\gamma = 0$, then the grower is "risk neutral," or indifferent to the volatility of his or her income stream.

Most importantly, by using an expected utility framework, we are able to estimate

¹³ Parameterizing the degree of risk aversion in the simulation model is not inconsistent with the risk-neutral derivative pricing model because risk neutrality in the latter case refers to the equilibrium market outcome, not an individual trader's attitude toward risk. In the simulation model, we assume that a representative grower need not have preferences identical to any other.

the risk premium placed by a representative grower on the threat of yield loss due to insect damage (or higher cost of insect control). Define a grower's certainty equivalent (CE) value as the dollar amount he or she would accept with certainty in lieu of the risky prospect of receiving an uncertain amount of net income with expectation $E[\pi_g]$. In a power utility framework, a grower's CE value is found by solving (9) for π_g . The risk premium grower g is willing to pay, therefore, becomes:

$$(10) \quad R(\pi_g) = E[\pi_g] - CE(\pi_g) \\ = E[\pi_g] - ((1 - \gamma)E[U_g])^{1/(1-\gamma)},$$

for an uncertain level of net income. For the *B. tabaci* example, net income from growing cotton is assumed to be equal to the difference between cotton revenue and total production cost, where revenue is the product of uncertain yields (y_g) and prices (p):

$$(11) \quad \pi_g = py_g - K(c_g),$$

and total production cost depends on the level of insect control activities, c_g . To capture the likely diminishing marginal returns to insect control activities, yield in year t is assumed to be a simple Cobb-Douglas (log-log) function of insect density, control activities, and a binary variable to account for year-specific population differences:

$$(12) \quad \ln(y_{g,t}) = \beta_0 + \beta_1 \ln(B_{g,t}) + \beta_2 \ln(c_{g,t}) \\ + \beta_3 D94 + \varepsilon_{g,t},$$

where $D94$ is a binary variable for the year 1994 ($D94 = 1$ if the year is 1994, and is zero otherwise); $\varepsilon_{g,t}$ is a grower-specific i.i.d. random error vector; and the remaining variables are as defined above.

Because we do not have data on other inputs, the yield function in (12) assumes all growers use best-practice technology so that β_0 represents their average yield, conditional on optimal input application.

Further, insect control, and hence populations, are assumed to be endogenous. Therefore, equation (12) is estimated using an instrumental variables procedure (two-stage least squares) where the set of instruments includes all exogenous and predetermined variables in the system. Because a least-squares procedure is used to estimate (12), we implicitly assume the error term ($\varepsilon_{g,t}$) is normally distributed. Consequently, the stochastic profit simulation model is driven by a Gaussian error process for yields, the parameters of which are determined from the estimation results.

The stochastic expected utility framework is then used to define three measures of the risk-return tradeoff generated by various risk management strategies: (a) a Sharpe ratio, (b) a 5% Value-at-Risk (VaR) measure, and (c) a certainty equivalent value.

The Sharpe ratio is a measure of return per unit of risk derived from an expected utility-maximization framework (Gloy and Baker, 2001). Specifically, it is defined as the ratio of excess returns to an asset to the coefficient of variation of its returns, where "excess returns" are defined relative to the risk-free rate of return. Formally, the Sharpe ratio is written as:

$$(13) \quad SR_g = \frac{R_g - R_f}{s_g / E[R_g]}$$

where R_g is the return to the asset or venture in question, R_f is the risk-free rate of return, s_g is the coefficient of variation of returns, and $E[R_g]$ is the mean return.¹⁴

Value-at-Risk (VaR) measures the maximum amount a firm can expect to lose at a certain confidence level for a certain period of time. For example, if a

grower's VaR is -\$200 per acre at 5% on an annual basis, this means there is a 5% chance he or she will lose at least \$200 during the year. VaR provides a very intuitive notion of the monetary equivalent of the risk facing a firm as it immediately converts a notion of spread or dispersion into a dollar-equivalent figure (Jorion, 1997).

Finally, the CE value defined in equation (10) is compared for alternative insect-risk management strategies. From a grower's perspective, a higher CE value is preferred because it implies a lower "cost of risk" or risk premium that a rational investor would demand.

By comparing each of these three measures between hypothetical scenarios wherein growers do or do not use insect derivatives, it can be determined whether bug options represent potentially valuable risk management tools.

A number of assumptions are made in order to implement the insect-derivative simulation model. First, the number of contracts used to hedge insect-yield risk from a typical acre of cotton in California's Imperial Valley (the "hedge ratio") is 1.89 (Cecchetti, Cumby, and Figlewski, 1988). The hedge ratio is determined by estimating a simple linear regression of yield on insect densities. The slope parameter in this regression shows the marginal impact of a one-adult-insect-per-leaf rise in population, so multiplying the marginal impact of one insect by the price of cotton provides an estimate of the marginal revenue-loss, or the hedge ratio.

Second, the insect process is assumed to be a linear function of control activities and other random factors:

$$B_{g,t} = \alpha_0 + \alpha_1 c_{g,t} + \varepsilon_{g,t},$$

where $\varepsilon_{g,t}$ is an i.i.d. normal error term. Again, given that $c_{g,t}$ is an endogenous variable, we use an instrumental variables technique in order to remove any simultaneous-equations bias.

¹⁴The financial return to a venture is defined as the ratio of net income, or profit, to the total amount of investment. We assume 100% equity financing throughout in order to abstract from decisions regarding the capital structure of the firm, which may introduce financial risk.

Third, to determine the independent effect of random insect growth on yields, the simulation is conducted with insect control activities held at their mean. While understanding the role of biological and chemical insect suppression is an important pursuit, the point of this research is to show how financial risk can be mitigated independent of traditional control methods.

Fourth, although cotton prices represent another source of economic risk in reality, prices are fixed at their long-term average—again in order to focus attention on the role of insect derivatives as a means of managing volumetric risk that arises from infestation.

Finally, the coefficient of relative risk aversion (γ) is allowed to vary from 0.1 (near-risk neutrality) to 0.9 (extreme risk aversion) to convey the importance of attitudes toward risk in determining the value of insect derivatives in terms of the expected-utility framework. The net income/expected utility model is simulated using Monte Carlo methods with @Risk stochastic simulation software (Pallade Corporation, 2005).

Results and Discussion

Recall, 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: (a) estimates of the deterministic insect population function; (b) estimates of the stochastic process that drives variation from the mean; (c) estimates of insect derivative price, herein defined as a call option on *B. tabaci* at the Brawley, California, site; (d) estimates of the impact of *B. tabaci* on cotton yields; and (e) simulation results regarding the feasibility of insect derivatives as risk management tools for insect-caused yield damage.

Table 2. Insect Population Mean Function Estimates (MLE), *Bemisia tabaci* Trial Data: Brawley, CA (1993–1994)

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
Log-Likelihood Function = -1,375.011		
χ^2 Statistic	= 1,694.820	

Notes: A single asterisk (*) denotes statistical significance at the 5% level. 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 the regression coefficient of the binary variable for the trials conducted in 1994 (1994 = 1 if the year is 1994, and 0 otherwise). The χ^2 statistic compares the estimated log-likelihood function model to a null alternative and has a critical value of 15.51 with eight degrees of freedom at a 5% level of significance.

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 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.

Table 3. Insect Stochastic Process Model Estimates (MLE), *Bemisia tabaci* Trial Data: Brawley, CA (1993–1994)

MODEL #1			MODEL #2			MODEL #3		
Brownian Motion (BM)			BM with Mean Reversion (BM-MR)			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 = -1,404.08			LLF = -1,305.16			LLF = -1,291.87		

Notes: A single asterisk (*) denotes statistical significance at the 5% level. The parameters are defined as follows: σ_t is the standard deviation of the Weiner process t ; μ_t is the drift rate of process t ; κ_t is the rate of mean reversion; λ_t is the arrival rate of the jump process; δ_t is the standard deviation of the jump process; and ϕ_t is the percentage deviation during a jump.

Next, estimates of the control function suggest that insecticide applications were subject to diminishing marginal returns each year. Nevertheless, 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 natural enemies, 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.

After removing the deterministic mean from the observed insect series, three alternative stochastic processes were then estimated in an attempt to explain the remaining, random variation. Starting with the simplest, most parsimonious model, we estimated: (a) a simple Brownian motion (BM); (b) a Brownian motion with mean reversion (BM-MR); and (c) a mean-reverting Brownian motion with discrete, Poisson-distributed jumps (BM-MR-J).

Table 3 reports 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 model selection.

For the first comparison (BM versus BM-MR), the resulting LR statistic is χ^2 distributed with one degree of freedom. At a 5% level, the critical χ^2 value is 3.84, while the test statistic value is 197.84. Thus, 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 χ^2 value is 26.58, again suggesting rejection of the more parsimonious model.

Based on these results, we therefore expect a drift rate away from the underlying trend of approximately one insect per leaf per week. Deviations from trend tend to return to the mean at a rate of 37% 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 *B. tabaci* growth, and so will be a major factor in pricing any derivative written for them.

Table 4. Insect Derivative Price Estimates Based on *Bemisia tabaci* Trial Data: Brawley, CA (1993–1994)

Strike Population	Call Option Value, V_c (\$)	Standard Deviation (\$)
20	46.37	7.44
25	41.44	7.91
30	36.99	7.65
35	31.73	7.54
40	24.94	7.99

Notes: Sample average population is 30.63 adults per leaf, so the first two call options are "in the money," while the third is "at the money," and the final two options are "out of the money" as the grower is better off with the expected number of insects than with that proposed in the hypothetical options with strike populations of 35 or 40 adults per leaf. Prices are obtained using the risk-neutral valuation method evaluated at the fixed parameter values given in Table 1. Monte Carlo simulations involve 10,000 draws from distribution of the random element in the insect population growth process.

Because the BM-MR-J model was found to dominate the others, we use this model to form expectations of the *B. tabaci* population value at contract expiry, as required by the pricing model in (8). Table 4 provides a summary of the price estimates for a range of strike population levels (20 adults per leaf to 40 adults per leaf) as well as their standard deviations.¹⁵

Conducting a sensitivity analysis of call option prices is necessary because the strike price is a significant element of the option contract that is subject to negotiation between both parties. Given that the average population value over the sample period is roughly 30 adults per leaf, options with strike populations above this value are termed "in the money" because they have a positive intrinsic value. In contrast, options with strike populations below 30 are "out of the money" because they have no intrinsic value to a potential purchaser. Further,

¹⁵ Strike population levels are chosen so that the mean density is approximately in the middle of the upper and lower values. The early 1990s represented a peak-infestation period for *B. tabaci* in this area; thus, these values are not intended to be representative of current conditions.

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 4 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 \$46.37. Because this price is fully justifiable on economic grounds, both the grower and counterparty (e.g., an insecticide company) will agree to this price and will enter the option contract willingly.

Given the equilibrium derivative prices in Table 4, we next examine whether a risk management program that incorporates insect derivatives is able to mitigate yield risk caused by insect infestation. According to equation (12), higher insect numbers reduce yields in a linear-quadratic manner, while chemical control activities affect insect numbers, and hence yield, in a similar fashion. Although this process is naturally recursive, because control activities do not affect yield directly but by reducing insect numbers, estimating with an instrumental variables procedure ensures that the parameter estimates are consistent. In this way, we control for the endogeneity of insect density and permit a direct estimate of the economic value of insect control.¹⁶ The yield equation forms the core of a stochastic profit-simulation model in which growers are able to offset insect-borne insect damage (i.e., lower yields) by purchasing insect call options from an anonymous third-party market-maker.¹⁷

¹⁶ In observed economic data, control activities would also be endogenous. However, in a controlled experiment, chemical applications are predetermined and thus not correlated with the error in each equation.

¹⁷ Commonly, derivative instruments that are not offered over a formal exchange are traded "over the counter" or between two parties in a privately negotiated transaction. A financial institution or trading firm (Bank of America is an example of the former, and Aquila Energy the latter) usually sells or "writes" the option for a party with a legitimate hedging interest taking the other side. Chemical companies may also sell options either directly to growers, or through financial market-makers.

Instead of offsetting the economic damage caused by insect infestation through derivative securities, clearly growers can also mitigate yield damage more directly through the use of chemical or biological treatment procedures. In the *B. tabaci* sample data, the intensity of insect control is measured by the number of applications of a fixed chemical regime throughout the growing season. However, allowing for chemical treatment means that growers can potentially manipulate the price of any derivative written on observed population counts. Therefore, to focus attention on the role and value of derivatives in the absence of such manipulation, we construct yield forecasts on the assumption that growers apply the sample-average number of treatments.¹⁸ This assumption is analogous to requiring growers who purchase multiple-peril crop insurance contracts to follow certain planting, growing, and harvesting restrictions in order to minimize the moral hazard problem.¹⁹

The yield model results are reported in Table 5. Based on sample average population values, the marginal effect of an additional adult *B. tabaci* 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. As also observed from this table, growers can reduce the damage from any given population level by spraying insecticide, but their ability to do so is subject to sharply diminishing marginal returns.

In order to implement the stochastic profit simulation model, it is also necessary to

¹⁸The number of treatments in the experimental data used here was not based on perceived need, but rather based on experimental protocol. Although actual treatment values will likely vary from those reported here, the estimated parameters are nonetheless estimated without bias.

¹⁹Moral hazard refers to the tendency of insured growers to reduce their efforts to avoid yield losses. By including "best practice" restrictions in derivative contracts, the counterparties are essentially reducing growers' ability to use insect derivatives to substitute for chemical control (as described earlier in footnote 3).

Table 5. Cotton Yield Model (2SLS), *Bemisia tabaci* Field Trial: Brawley, CA (1993–1994)

Parameter	Estimate	t-Ratio
Constant	7.066*	32.129
ln(<i>B</i> _{<i>t</i>})	-0.084*	-2.891
ln(<i>c</i> _{<i>t</i>})	0.166*	4.036
1994	0.292	1.341

$R^2 = 0.747$

Notes: A single asterisk (*) denotes statistical significance at the 5% level. Dependent variable = ln(Yield); independent variables are *B* = insect population, and *c* = level of control activities (number of applications). Instruments consist of all exogenous and predetermined variables in the system.

estimate the parameters of the Gaussian yield-error process. As required by the least-squares estimation procedure, the error process is indeed normally distributed with a mean of zero.

However, yield-risk in Imperial Valley cotton is significant, as the standard deviation is 138.7 pounds of cotton. This yield model, and the estimated error distribution, are then used as the primary inputs to the stochastic profit simulation model.

Table 6 shows the "base case" risk-return measures, under which no risk management activities are used, as well as those calculated under a simple risk management strategy. Although a wide range of derivatives can be defined, as well as strategies for trading them, we focus on an insect-derivative hedge in which the grower buys a call option with a strike population level equal to the average insect population value in the Brawley sample data set. As would be expected, if the options are fairly priced, net income does not differ between the hedge and no-hedge strategies in the simulation exercise (1,000 draws from the insect model error distribution).

The results reported in Table 6 show that the insect derivative provides a clear improvement in all risk and risk-return measures. Specifically, the Sharpe ratio under the hedge strategy is 0.15 points higher than in the unhedged scenario.

Table 6. Risk Management with Insect Derivatives Stochastic Simulation Results: Representative Cotton Farm, Imperial Valley, CA (2004)

Risk Metric	Risk Management Strategy	
	No Hedge (\$/acre)	Call Option Hedge (\$/acre)
Net Income	\$165.54	\$165.54
Sharpe Ratio	1.99	2.14
VaR (5%)	\$30.33	\$117.95
Certainty Equivalent:		
$\gamma = 0.1$	\$163.72	\$164.32
$\gamma = 0.5$	\$153.18	\$160.01
$\gamma = 0.9$	\$128.07	\$156.46
Risk Premium:		
$\gamma = 0.1$	\$1.82	\$1.23
$\gamma = 0.5$	\$12.37	\$5.54
$\gamma = 0.9$	\$37.47	\$9.08

Notes: Simulation results are from 1,000 random draws from normal insect population model error distribution with mean zero and standard deviation of 0.85 adults per leaf. Sharpe Ratio is defined as the excess returns (expressed as a percentage of invested capital) over the risk-free rate divided by the coefficient of variation of returns. VaR is the "value at risk" and is interpreted as the maximum loss expected with a 5% probability. Certainty equivalent and risk premium values are calculated from the power utility function with a coefficient of relative risk aversion of γ , where $\gamma = 0.1$ indicates near-risk neutrality, $\gamma = 0.5$ is moderate risk aversion, and $\gamma = 0.9$ is strong risk aversion. All simulation data are taken from University of California Cooperative Extension (2005).

Therefore, purchasing an at-the-money call option provides a favorable risk-return tradeoff relative to relying on chemical or biological control methods alone.

Subtracting the 5% VaR from expected net income provides a measure of how much a grower can expect to "lose" relative to a normal year 5% of the time, or one year in 20. Because low yields are driven entirely by insect damage in this model, this "worst case" scenario means a year with a particularly high number of insects. With no options hedge, a grower can expect to lose \$135.21 (= \$165.54 - \$30.33) 5% of the time relative to average net income. With a call-options hedge, however, the expected loss falls to \$47.59 (= \$165.54 - \$117.95) because the insect option

effectively truncates the revenue distribution below the point at which insect damage would otherwise cause significant yield losses.

Unlike the previous measures, a grower's certainty equivalent (CE) value depends upon his or her attitude toward risk, here summarized by the coefficient of relative risk aversion. Higher values of γ mean the grower is more risk averse, and so is willing to pay less for a risky prospect. At values of γ near risk neutrality ($\gamma = 0.1$), the difference in CE values between the hedged and unhedged scenarios is small. However, as the degree of risk aversion rises toward 0.9, the difference in CE values rises as our representative grower attaches a greater value to the stability of net income, relative to the magnitude.

Finally, the difference between net income and CE for each level of risk aversion gives the risk premium—or the amount a grower would willingly pay for insurance sufficient to remove any remaining net income risk. According to these simulation results, trading insect call options removes a significant part of the risk premium associated with growing cotton. Whereas a risk-averse grower who does not buy a call option can be expected to pay a \$37.47 premium to transfer all yield risk, call option buyers are expected to pay an average of only \$9.08. Based on these aggregate results, therefore, it is clear that insect derivatives can be effective in mitigating the economic risk caused by insect infestation.

Conclusions and Implications

Findings from this analysis reveal it is possible to design a financial instrument that allows growers to transfer the financial risk of insect damage to their crop. Further, because data on insect populations are readily available through rigorous scientific experimentation for many systems, it is possible to value derivative contracts written for a specific crop and location. Indeed, because insect numbers are independent of financial

markets or other measures of broader economic performance, it is possible to use relatively simple risk-neutral valuation methods to price a wide range of insect derivatives.

As shown by this study, insect derivatives, designed according to the principles outlined here, can be effective risk management tools. Although derivatives must be purchased from a counterparty who is willing to assume the risk that is transferred, the cost is generally more than offset by the higher utility derived from a less volatile income stream. This is found to be the case for a particular type of derivative—a call option on the underlying insect population—but it remains to be demonstrated for other types of derivatives and for other insect populations.

Further work in this area is required in order to develop a better understanding of the practical aspects associated with creating and trading insect derivatives.

- First, although we have shown 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 the grower's risk management strategy with insect derivatives. In particular, the valuation method considered here 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. By explicitly linking population growth rates at varying distances, and with varying degrees of contiguity relative to one another, we will be able to price variation in both dimensions. This research represents an advance in both economic entomology and derivative pricing more generally, as it offers a means of explicitly pricing spatial basis risk.

Another method of addressing basis risk is to use an algorithm based on the concept of forecast encompassing. With this approach, traders create optimal cross-hedges in the presence of spatial basis risk using contracts written on different insect monitoring stations, where optimality is defined in terms of the weight placed on contracts written at different locations. This method was developed by Sanders and Manfredo (2004) for determining the relative weights to place on different futures contracts in a composite hedge. By taking optimal positions in several different insect trap locations, traders will be able to create a portfolio that best mimics the risk at their particular location. While not likely to eliminate all basis risk, forecast encompassing offers an econometric-based means of creating effective hedge positions for traders.

- Second, while insect populations under the controlled conditions of the data used in this study do not appear to change with respect to heat or precipitation (see footnote 5), other insect and invasive species, including plants, nematodes, fungi, and locusts, do respond to specific weather conditions. Thus, in addition to the "bug options" presented here, there are a host of other possibilities, including a variety of weather derivatives, which could be used to offset economic losses to crops caused by insects.
- Third, more research should be conducted using other insect species to determine whether the growth processes estimated in this analysis are typical of insects in general, or if *B. tabaci* represent somewhat of an anomaly. This consideration is particularly important given that the densities of *B. tabaci* during the experimentation period used here were likely much higher than those experienced currently.
- Fourth, 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 led 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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Appendix: Solution to Exponential Growth Equation

To solve the differential equation in (1) of the main text, use the separation-of-variables principle to rewrite as:

$$(A1) \quad \frac{dB}{B(K-B)} = \frac{\alpha_1}{K} dt,$$

after simplifying notation for the mean bug process. Next, rewrite this expression as:

$$(A2) \quad \left(\frac{1}{B} + \frac{1}{K-B} \right) dB = \alpha_1 dt,$$

and integrate both sides to obtain:

$$(A3) \quad \ln \left(\frac{B}{K-B} \right) = \alpha_1 t + \ln \left(\frac{B_0}{K-B_0} \right).$$

Next, solving for B gives:

$$(A4) \quad B = \frac{K}{1 + de^{-\alpha_1 t}},$$

where $d = (K - B_0)/B_0$. In the text, the control function g is assumed to be exogenous to the natural growth process described by the differential equation in (1), as given by (A1) above.