Market-Based Instruments for the Optimal Control of Invasive Insect Species: *B. Tabaci* in Arizona[*]

Timothy J. Richards, Peter Ellsworth, Russ Tronstad and Steve Naranjo

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[*] Richards is Morrison Professor in the Morrison School of Management and Agribusiness, Arizona State University; Ellsworth is Professor in the Department of Entomology, University of Arizona; Tronstad is Professor in the Department of Agricultural and Resource Economics, University of Arizona, and Naranjo is Senior Research Scientist in the Agricultural Research Service, USDA, Maricopa Agricultural Center. Contact author: Richards: 7171 E. Sonoran Arroyo Mall, Peralta 335U, Mesa, AZ. 85212. Ph. 480-727-1488, FAX 480-323-2294, email: trichards@asu.edu. Funding from ERS-PREISM grant no. 58700080123 is gratefully acknowledged. Copyright 2010 by Timothy J. Richards. All rights reserved. Readers may make verbatim copies of this document for non-commercial purposes by any means, provided that this copyright notice appears on all such copies.

Abstract:

Invasive insect species represent perhaps one of the most significant potential sources of economic risk to U.S. agricultural production. Private control of invasive insect species is likely to be insufficient due to negative externality and weaker-link public good problems. In this study, we compare a system of Pigouvian taxes with tradable permits for invasive species control. While the emissions control literature shows that taxes are preferred to permits under cost uncertainty, invasive species control involves correlated cost and benefit uncertainty, so we expect a quantity-based system to be preferred. Monte Carlo simulations of optimal steady-state outcomes confirm our expectations.

keywords: externalities, invasive species, optimal control, permits, spatial-temporal model, taxes.

JEL Codes: H23, L51, Q28, Q57.

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Introduction

Invasive insect species represent a significant economic risk to both the financial viability of agricultural producers and to the sustainability of U.S. agriculture more generally. With the rapid growth of international trade in agricultural commodities of all types, agricultural systems in the U.S. are under constant threat that new species will be introduced, spread and thrive in an environment lacking natural predators. Indeed, Pimentel, Zuniga and Morrison (2005) claim that insects alone are responsible for losses amounting to 13% of total U.S. crop production, valued at \$33.0 billion.[**] According to these authors, 40% of all insects can be regarded as invasive. Therefore, including the indirect costs associated with control, the total damage attributable to invasive insect species in the U.S. is \$13.5 billion in 2001 dollars.

In the absence of alternative institutional mechanisms, private market incentives to control invasive species are likely to be insufficient from a social perspective for two reasons: (1) control provides a positive externality to others (or a lack of control confers a negative externality), and (2) pest-free environments are public goods (Knowler and Barbier, 2005; Burnett, 2006). First, if one grower does not control his or her insects, others will experience higher control costs. The fact that these external costs are not reflected in his or her decision regarding the level of suppression means that each grower will invest in too little pest management. Second, invasive species control is a weaker-link public good (Cornes, 1993) in

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[**] Alien-invasive species include plants, mammals, birds, pathogens, insects and a number of other organisms. In this research, we focus on insects that are uniquely harmful to agricultural crops. Our methods and tools, however, are directly applicable to other forms of invasive species as well.

that a grower is likely to appropriate some of the pest-reduction benefits from controlling insects on his or her own land, but will not achieve ideal control if neighboring growers do not control as well. In this study, therefore, we investigate two market-based institutional mechanisms for invasive species control: a system of taxes on insect population numbers, and a marketable permit system that allows each grower only a certain amount of infestation.

Invasive species management programs that involve direct government control are neither practical, desirable nor efficient (Costanza and Perrings, 1990; Cornwell and Costanza, 1994). Fortunately, there are a number of market-based options that have proven workable. First, Knowler and Barbier (2005) argue that a system of Pigouvian taxes may be able to achieve the optimal balance between controlling the damage from an invasive species and encouraging the diversity benefits that follow from importing species that are not native to North America. However, taxes are still regulatory in nature as they require a taxation authority to design, administer and enforce their payment. Costanza and Perrings (1990) and Cornwell and Costanza (1994) offer a system of performance bonds that provide for financial penalties if environmental goals are not met. Shogren, Herriges, and Govindasamy (1993), however, point out that bonds suffer from a number of practical limitations such as moral hazard, liquidity problems and legality. Horan and Lupi (2005), on the other hand, describe a system of tradeable "risk permits" written on the probability that any ship entering the Great Lakes is likely to import a species that may ultimately become invasive. However, they show that the first-best system of permits will not work because of the heterogeneity among ships in terms of their cost of avoiding the release of a potentially invasive organism. In this study, we consider two of these options: a tax on adult insects measured at a certain point in time on each farm, or a permit system that provides for overwhelming penalties if the allowed population is breached. Growers, however, will be able to trade permits such that those with lower control costs can sell permits to other, relatively high control-cost growers.

There is a large literature that compares the efficiency of taxes and permits as alternative means of externality control in the context of carbon pollution and greenhouse-gas (GHG) accumulation. It is well understood that, under certainty, taxes and permits produce the same outcome in terms of emission control (Baumol and Oates, 1988). However, Weitzman (1974) shows that, under uncertain control costs, taxes are preferred when the marginal social benefit of controlling emissions is relatively flat, and the marginal cost of abatement steep. However, a quantity-based system of controls, such as a permit-based system, will be preferred if the marginal social benefit curve is steep, and marginal control costs relatively constant. Importantly, uncertainty regarding marginal benefits is irrelevant to the choice of instrument. Hoel and Karp (2001, 2002), Pizer (2002), Newell and Pizer (2003), Karp and Zhang (2005) extend this logic to the case of stock externality where regulation takes place in a dynamic environment. These studies confirm the Weitzman intuition in analytical models of quadratic abatement cost and multiplicative uncertainty and, moreover, show that a price-based policy (taxes) is preferred in a welfare-metric sense over permits. In a static framework, Stavin (1996) shows that correlated cost and benefit uncertainty reverses this result and leads to a preference for a quantity-based system under realistic parameter assumptions. In this study, we extend the logic of Stavin to the case of spatial-temporal uncertainty and also show that the Weitzman result is reversed. In this case, a quantity-based system of regulation is preferred to a price-based system. This outcome is fortuitous from a regulatory perspective, because a permit system is likely to be both politically and administratively easier to implement than a system of taxes.

The objective of this study is to investigate whether taxes or permits is preferred for the control of spatial-temporal externalities that arise in the management of invasive insect species. We apply our model to a specific insect – *Bemisia tabaci*, or whitefly, in Arizona. Welfare outcomes are compared under scenarios of only privately-optimal insect control, private control with taxes, and private control with permits relative to a socially-optimal benchmark. We compare steady-state solution paths and social welfare under both certainty and uncertainty to determine whether the insights of Weitzman, Stavins, Hoel and Karp (2001, 2002) and Newell and Pizer hold in a model of spatial-temporal insect movement and dispersion.

The paper is organized as follows. In the next section, we provide some background on the object of our study – whitefly in Arizona. The second section describes an economic model of optimal spatial-dynamic control of whitefly that incoporates the elements of market failure described above. A third section outlines our empirical approach to parameterizing the optimal control model, and the data required to generate equilibrium steady-state control paths. The data used to estimate and simulate the optimization model is described in the fourth section, while the fifth presents the findings of the empirical study and offers some practical implications for invasive species management policy. The final section concludes and offers some suggestions for future research in this area.

Background on Whitefly: Q-biotype *B. tabaci*

We focus on one of the most nefarious, invasive insect species in Arizona, the whitefly (Q-biotype *Bemisia tabaci*). While the B-biotype *B. tabaci* is arguably not invasive, having been identified as a significant economic pest at least since 1981 (Oliveira, Henneberry and Anderson, 2001), the Q-biotype was discovered in a commercial greenhouse in Tucson in only 2005 (Dennehy, et al., 2006).

Q-biotype *B. tabaci* is particularly troublesome due to its resistance to a number of insecticides that have proven effective in controlling B-biotype. *B. tabaci*, in general, is a uniquely harmful insect to either cotton or nursery crops. First, *B. tabaci* is polyphagous, meaning that it feeds on many types of food so is able to move from host to host as cropping cycles evolve (Watson, et al., 1992; Oliveira, et al., 2001). Second, the whitefly has proven to be remarkably adaptable to poor host plant conditions through natural selection over only a few generations (Basu, 1995) and travels rapidly from host to host, often over considerable distances through commercial transportation or weather patterns (Ellsworth and Martinez-Carrillo, 2001). Third, it is an important vector for a range of viruses that are known to be the source of several common diseases in tomatoes, beans, cassava, and most important to Arizona, cotton and lettuce (Watson, et al., 1992; Oliveira, et al., 2001). Fourth, Dittrich et al. (1990) document the ability of *B. tabaci* to develop resistance to common insecticides and, indeed, to increase the rate of egg-laying when under stress from insecticides. Finally, the destructive nature of *B. tabaci* can mean the elimination of entire cropping systems once infestation occurs. Therefore, finding an effective and efficient means of control is an economic imperative for Arizona agriculture.

Economic Model of Whitefly Control

In this section, we describe a spatial-temporal optimal control model of whitefly management that focuses on the externalities caused by insect growth and migration. Invasive species control is inherently spatial-temporal because two forms of externality are involved: (1) a dynamic externality that arises due to population growth over time, and (2) a spatial externality that arises due to migration. Unlike the case of pollution control, invasive species cause damage to both farms that serve as hosts, and the growing community more generally. The externality arises due to the fact that insects migrate from one farm to the next, so a level of control that may be optimal from a private perspective is not likely to be optimal from the perspective of the community as a whole.

Assume that there is one firm located at each location (s) in a grid structure in which distances between firms are measured from centroid to centroid.[***] From the firm's perspective, the optimization problem is written as:

$$V^f = \underset{x_{st}}{Max} \int_0^\infty e^{-\rho t}[(p_t - c_{st})y(b_{st}) - k(b_{st}, x_{st})]\,dt, \quad \forall\, s \in \theta, \tag{1}$$

where V^f is the present value of the firm, ρ is the rate of discount, p_t is the price of output, c_{st} is the marginal cost of production, y is the yield, b_{st} is the population of insects at location s and time t, x_{st} is the level of control and k is the control cost function. Control costs are convex in the population level and control such that: $k_b > 0$, $k_x > 0$, $k_{bb} > 0$ $k_{xx} > 0$, and $k_{bx} < 0$. Equation (1) is solved subject to the equation of motion for b_{st} which is given below.

[***] Clearly, this assumption is necessary to make the problem analytically tractable, but ignores border issues, nearest-neighbor effects and the likelihood that insects are distributed more continuously over the relevant geography than a grid structure would imply.

Solving the Planner's Problem

The planner's problem, on the other hand, is to maximize the value of production across all locations, net of control and social damage costs, V^p, by choosing control activity-levels at each point in space and continuously over time according to:

$$V^p = \underset{x_{st}}{Max} \int_0^\infty e^{-\rho t} \sum_{s \in \theta} [(p_t - c_{st}) y(b_{st}) - D(ND_s(b_{1t}, b_{2t}, \ldots b_{St})) - k(b_{st}, x_{st})] \, dt, \qquad \textbf{(2)}$$

where D is a "social damage function" that reflects the damage inflicted on others' crops from net dispersion (ND_s) from location s to all other locations (Smith, Sanchirico and Wilen, 2009). For simplicity, we assume the industry is comprised of n identical firms so we can aggregate the solution to (1) to compare directly to the socially optimal solution. We assume that both the firms and the regulator take output and input prices as parametric. All firms are located at different points in a discrete space transcribed by the set of grid points θ.

Entomologists recognize that invasions of new pest populations tend to follow a three-phase process: (1) arrival, (2) establishment and (3) spread (Hof, 1998; Leibhold et al., 1995). Therefore, equation (1) is solved subject to spatial-temporal equations of motion that govern *B. tabaci* growth and dispersion within the sample data set.

The equation of motion for insects at each point (on one farm) is relatively simple. Insect numbers grow as a function of the existing population, less removals due to control activities:

$$\frac{\partial b_{st}}{\partial t} = g_{st}(b_{st}) - x_{st}, \tag{3}$$

where the specific form of the growth function, $g_{st}(b_{st})$, is specified below. The planner, however, must also take into account the spatial externalities associated with movement from one location to the next. The random nature of the spatial-temporal diffusion of *B. tabaci* is described using a general diffusion model wherein the rate of population growth at a point consists of an autonomous growth component, migration from other locations and planned removals through control activities. The rate of diffusion, in turn, depends on the population at the point, its distance from an initial point and the rate of diffusion so that the general form of the state equation is written:

$$\frac{\partial b_{st}}{\partial t} = g_{st}(b_{st}) + \frac{\partial}{\partial s} G \frac{\partial b_{st}}{\partial s} - x_{st} = g_{st}(b_{st}) + G \frac{\partial^2 b_{st}}{\partial s^2} - x_{st}, \tag{4}$$

where G is the diffusion coefficient that governs the rate of spatial movement. Equation (4) is Fisher's reaction-diffusion equation in general notation.

Consistent with the discrete nature of the space described in (2), we follow Sanchirico and Wilen (2005) by assuming whitefly make discrete movements from one location to the next, on the assumption that each grower is located at one point on the spatial grid defined by the set θ. The change in population from one period to the next at each point in space, therefore, consists of autonomous growth, net dispersal (in migration less out migration), and insect removals:

$$\frac{\partial b_{st}}{\partial t} = g_{st}(b_{st}) + ND_s(b_{1t}, b_{2t}, \ldots b_{St}) - x_{st}, \qquad \textbf{(5)}$$

where ND_s is the net dispersal function. In Fisher's equation, growth is governed by a relationship that depends on the current population and the population relative to carrying capacity:

$$g_{st}(b_{st}) = r_s b_{st}(1 - b_{st}/K_s), \qquad \textbf{(6)}$$

where r_s is the intrinsic growth rate, and K_s is the carrying capacity of location *s*. Next, we approximate the net dispersal function with an additive function that accounts for all in-migration and out-migration such that:

$$ND_s(b_{1t}, b_{2t} \ldots b_{St}) = \sum_{j=1}^{S} d_{js} b_{jt}, \qquad \textbf{(7)}$$

where d_{js} are coefficients that represent the movement from location *j* to location *s* as a share of the total population (Sanchirico and Wilen, 2005). Depending on the location in space, and time since introduction, in-migration can either be positive or negative.

We then follow Hof and Bevers (2000) and calculate each of the d_{js} elements using Fick's Law. Others, including Liebhold, et al.; Hof; Burnett, Kaiser and Roumasset, and Richards, et al. (2009) combine Fick's Law with an exponential growth component to arrive at a continuous-time dispersion and growth model (Skellam, 1951). However, exponential growth for an insect species on one plot of land is not realistic. Therefore, the dispersal coefficients are calculated using:

$$b_{st} = b_{s_o t_o}\left(\frac{e^{-q^2/4Gt}}{2\sqrt{\pi G t}}\right), \qquad \textbf{(8)}$$

for an initial point in space and time (s_o, t_o) and an estimated diffusion rate, G, for each discrete location during each time period. According to Fick's Law, the spread of an invasive insect from a starting point s_0 is normally distributed with a rate of dispersion given by G. Because the rate of dispersion is host-dependent among polyphagous insects, we model the ability of *B. tabaci* to transition between cotton seasons on hosts other than cotton by allowing G to depend on the host, h (Smith, Sanchirico and Wilen) where the variable h is a qualitative indicator that essentially allows the rate of dispersion to vary with the attributes of each location: $G(h)$. Further, the impact of varying crop location relative to a source of infestation is modeled through the variable q, which is a continuous measure of the distance of a population at point s from one at s_0. Including the control activity, the equation of motion then becomes:

$$\frac{\partial b_{st}}{\partial t} = \dot{b}_{st} = r_s b_{st}(1 - b_{st}/K_s) + \sum_{j=1}^{S} d_{sj} b_{jt} - x_{st}, \qquad \textbf{(9)}$$

for each location s and time t.

We first solve the problem from a planner's perspective. Recall that by defining the problem such that each discrete location in space is a "farm," the planner's problem internalizes all of the spatial externalities implied by movement of insects from one location to the next. Although highly stylized, this solution captures the nature of the externality that we wish to describe, and to control. We first solve the problem under certainty, assuming the net dispersal amounts are known with certainty, and then move to a stochastic solution in which movement is determined by random draws within the Fisher equation structure. We solve the planner's problem by apply Pontryagin's maximum principle to the objective function above, on the assumption that each location represents a different, but connected, sub-problem. That is, the optimal population path and control policy will depend on the growers' location in space.

The Hamiltonian for the planner's problem at each location, *s*, is written as:

$$H(x_{st}, b_{st}, \lambda_{st}; \theta) = (p_t - c_{st}) y(b_{st}) - D(ND_s) - k(b_{st}, x_{st}) + \lambda_{st}(g_{st}(b_{st}) + ND_s - x_{st}), \quad \textbf{(10)}$$

in general notation where the arguments of the net dispersion function have been suppressed for clarity, where λ_{st} is the costate variable associated with the insect population at each location, *s*, and time period, *t*. Assuming an interior solution, the first-order conditions to this problem are given by the optimal choice of insect control:

$$\frac{\partial H}{\partial x_{st}} = -k_{x_{st}} - \lambda_{st} = 0, \quad \textbf{(11)}$$

the costate equation:

$$\dot{\lambda}_{st} - r\lambda_{st} = \frac{-\partial H}{\partial b_{st}} = -[(p_t - c_{st}) y_b - \sum_j D'(ND_b) - k_b + \lambda_{st}(g_b + ND_b)], \quad \textbf{(12)}$$

where *D'* is the incremental external damage associated with the movement of one insect from location *s* to locations *j*, subscripts indicate partial differentiation at each location *s* and time period *t*, and the spatial-temporal constraint on insect growth at each location:

$$\frac{\partial H}{\partial \lambda} = g(b_{st}) + ND(b_{st}) - x_{st}, \tag{13}$$

in addition to the usual transversality and non-negativity constraints. These first order conditions imply that the current value of any increment to future insect populations, at each location, must be equal to the marginal cost of reducing the population by one insect and the marginal social damage inflicted on the rest of the growing community associated with migration from location s.

For purposes of this paper, we are interested only in the characteristics of the steady-state solution and the welfare implications of the implied long-run industry equilibrium. The optimal steady-state solution for the number of whitefly at location *s* and time *t* is:

$$b_{st}^{*} = (K_s/r_s)(x_{st} - \sum_{j \neq s} d_{sj} b_{jt} - d_{ss} - 1), \tag{14}$$

while the optimal solution for the amount of whitefly control at each location and point in time is given by:

$$\begin{aligned} x_{st}^{*} &= (1/k_{xb})((p_t - c_{st})y_b - \sum_j D'(ND_b) - k_b + k_x(r_s(1 - b_{st}/K_s) - \\ &\qquad r_s(b_{st}/K_s) + \delta + \sum_j d_{sj}) + k_{xb}(r_s b_{st}(1 - b_{st}/K_s) + \sum_{j \neq s} d_{sj} b_{st}) \\ &= (1/k_{xb})((p_t - c_{st})y_b - \sum_j D'(ND_b) - k_b + k_x(g_b + ND_b + \delta) + k_{xb}(g + ND), \end{aligned} \tag{15}$$

where the *x* and *b* subscripts refer to partial differentiation with respect to insect control and population levels, respectively. Solving for the steady-state value of the costate variable gives:

$$\begin{aligned}\lambda_{st}^{*} &= (1/\delta)((p_t - c_{st})y_b - k_b - \sum_j D'(ND_b)_j + k_x(r_s(1 - b_{st}/K_s) - \\ &\qquad r_s(b_{st}/K_s) + d_{ss} + \delta) - \sum_{j \neq s} k_x d_{js}) \\ &= (1/\delta)((p_t - c_{st})y_b - k_b - \sum_j D'(ND_b)_j - k_x(g_b + ND_b + \delta) - \sum_{j \neq s} k_x d_{js})\end{aligned} \tag{16}$$

These three sets of equations (3S equations) are solved simultaneously for the optimal whitefly population (b_{st}), management policy (x_{st}) and value of the costate variable (λ_{st}). Because we include net dispersals in this solution, however, it describes the social optimal solution and not the one expected to be generated by the private market. Again, assuming there is one grower located at each point, *s*, on the grid, he or she will not take into account the externality associated with insect movement to other locations.

Solving the Firm's Problem

Clearly, the solutions to the firm's and the planner's problems above differ to the extent that the former does not take into account the externality created by the spatial migration of insects from one property to the next. Each grower only controls insects until the marginal value of damage inflicted on his or her own crops is equal to the marginal cost of control, including future growth on the grower's own land. However, other growers are negatively impacted to the extent that some of the population growth native to a grower's own fields ultimately migrates to others' fields according to the net dispersal function. In this section, we show that grower-specific taxes on the external damage caused by this migration can provide sufficient incentives for an optimal amount of control, as can a direct limit on insect population that is managed through a system of marketable permits. In this case, the permit price in equilibrium will be equal to the optimal Pigouvian tax levied on insect numbers above an allowable threshold. In the simplest case, the equivalency of taxes and permits shown by Baumol and Oates and a number of others holds exactly.

Several studies (Weitzman; Roberts and Spence, 1976; Adar and Griffin, 1976; Yohe, 1977) show, however, that this is no longer the case when there is uncertainty regarding the cost of pollution reduction and that benefit uncertainty is irrelevant. Moreover, with uncertainty if the slope of the marginal social benefit function is relatively flat or if the slope of the marginal-abatement cost function is relatively steep, then price-based policies will be preferred. If the opposite is true, then permit, or quantity-based policies will be more effective and efficient. The intuition is straightforward. If the benefit function is relatively flat, then errors in estimating the marginal cost function will cause only small deviations from the optimal solution if a policy is used that fixes the marginal social damage level. On the other hand, if permits fix the amount of effluent and the realization of the cost function is far different from that expected when the policy was put in place, then the deviation in the resulting marginal social damage will be large.

More recent research extends this reasoning to a dynamic context. These studies show that there are many reasons why taxes and permits are not equivalent in the control of stock externalities (Requate, 1998; Hoel and Karp, 2001, 2002; Karp and Zhang; Newell and Pizer, and others). It is well understood that in the case of stock externalities (pollution accumulates over time so that emissions during each time period add to the stock of pollution, and it is the stock of pollution that causes the damage) taxes and permits will not be equivalent as taxes are assumed to be fixed over time and permit prices can vary as the cost of abatement (control) changes.

Further, in a static environment Stavins shows that correlated uncertainty between benefits and costs creates a preference for quantity-based regulation. It is our hypothesis that a similar variance outcome arises when the externality is spatial and taxes (the first-best solution) are levied on a grower-by-grower basis. In this case, taxes are assumed to be location-specific and fixed in a spatial sense. This fixes the marginal social damage for each location. In a permit system, however, the allowable insect count is fixed for each location and permit prices are allowed to vary, thus allowing the marginal social damage to depend on production and infestation conditions at each location. Permits will be traded within each period to remove any arbitrage possibilities and thus equate the marginal social damage across locations. Permit trading, therefore, results in a more efficient outcome for the community as a whole and, we expect, greater social welfare relative to a system of taxation.

We first compare the socially-optimal solution above to the privately-optimal solution with a system of taxes. Because the externality arises due to net dispersions from each farm, we modify the social problem such that the social damage function is no longer part of the objective function. The optimal solution under a location-specific (first-best) tax regime is found by including a tax on net dispersals ($ND_s(b_{st})$) in the objective function introduced above. With this change, we write the current value Hamiltonian as:

$$H(x_{st},b_{st},\lambda_{st};\theta) = (p_t - c_{st})y(b_{st}) - k(b_{st},x_{st}) + \tau_{st}ND_s + \lambda_{st}(g_{st} + ND_s - x_{st}), \qquad \textbf{(17)}$$

where τ_{st} is the Pigouvian tax for location *s* at time *t*. The first-order conditions are modified to include the new costate equation:

$$\dot{\lambda}_{st} - r\lambda_{st} = \frac{-\partial H}{\partial b_{st}} = -[(p_t - c_{st})y_b - k_b - \tau_{st}ND_b + \lambda_{st}(g_b + ND_b)], \tag{18}$$

so the optimal solution for the steady-state control level by a private firm facing tax rate τ_{st} becomes:

$$x_{st}^* = (1/k_{xb})((p_t - c_{st})y_b - k_b - \tau_{st}ND_b + k_x(g_b + ND_b + \delta) + k_{xb}(g_{st} + ND_{st}), \tag{19}$$

again simplifying notation. Analogous changes to the optimal steady-state for insect population numbers and co-state values are obvious so are not reported here. Comparing the socially optimal solution to the solution with tax, the optimal tax is simply: $\tau_{st} = k_{x_{st}}$, in the first-best solution as the marginal damage of an insect that moves from one location to the next is simply the marginal cost of controlling that insect once it arrives at its destination.

Next, we compare the solution with taxes to one that places a quantitative restriction on the number of whitefly at each location, and allows growers to trade permits. In this case, growers can either control insects that would migrate from their farm to the next, or they could buy permits to allow more insects to remain on their land. Assuming that the location-specific limit on insects is given by $\overline{ND}_{st}$ the Hamiltonian above is replaced by:

$$\begin{aligned} H(x_{st}, b_{st}, \lambda_{st}, \pi_{st}; \theta) = (p_t - c_{st})y(b_{st}) - k(b_{st}, x_{st}) + \\ \lambda_{st}(g_{st} + ND_{st} - x_{st}) + \pi_{st}(\overline{ND}_{st} - ND_{st}), \end{aligned} \tag{20}$$

where π_{st} is the multiplier associated with the insect restriction, or the marginal value of obtaining one more license for whitefly. Solving this problem for the optimal amount of whitefly control, we find that the costate equation now includes:

$$\dot{\lambda}_{st} - \delta\lambda_{st} = \frac{-\partial H}{\partial b_{st}} = -[(p_t - c_{st})y_b - k_b + \lambda_{st}(g_b + ND_b) - \pi_{st}ND_b], \qquad \textbf{(21)}$$

which yields a steady-state solution for the control variable:

$$x^*_{st} = (1/k_{xb})((p_t - c_{st})y_b - k_b - \pi_{st}ND_b + k_x(g_b + ND_b + \delta) + k_{xb}(g_{st} + ND_{st}). \qquad \textbf{(22)}$$

The equivalence between taxes and permits is apparent from comparing (22) and (19) and noting that $\pi_{st} = \tau_{st}$ in equilibrium.

Despite this equivalency result, it is not clear whether the similarity of the steady-state solutions means that they provide the same welfare results when we explicitly account for the uncertainty inherent in the spatial-temporal movement of insects. In Newell and Pizer and Hoel and Karp (2001, 2002), uncertainty in stock regulation is introduced through the cost of control. This is reasonable in the case of effluent regulation as the amount of production is under managerial control and, presumably, they are aware of the relationship between output and effluent from their plant. Uncertainty is attributed to regulators' imperfect knowledge regarding this relationship and is thus understandable.

In the invasive species case, however, the nature of the externality is fundamentally different. Namely, both the benefit and cost of control depend on the biology of insect movement, so both are inherently uncertain. First, the arrival time of an invasive insect is never known with certainty. Typically, this type of *a priori* uncertainty is modeled using a hazard function approach in which the probability of arrival rises the longer the particular area has been insect-free. Second, once arrival occurs movement involves both dynamic and spatial uncertainty. The diffusion model developed above captures this uncertainty directly and implicitly as the insect population at any given location is known only up to the normal probability distribution that characterizes the Fisher equation.

Consequently, while the uncertainty in Weitzman, Hoel and Karp (2001, 2002), Karp and Zhang and Newell and Pizer derives from the cost of pollution abatement, the uncertainty in the current model comes from both the cost of control and the movement of insects from one location to the next. As long as insects arrive and move according to biological growth processes, problems of invasive species management will always be subject to a significant amount of uncertainty – uncertainty that affects both the benefit and the cost of regulation. Moreover, the impact of population uncertainty on the cost and benefit side is likely to be correlated so the analysis of Stavins applies to the invasive species problem, but in a spatial-temporal, rather than static, context. For this reason, we consider the welfare effects of taxes and permits when whitefly dispersion is subject to correlated uncertainty, conditional on their having already arrived.[****]

Rather than derive an analytical expression for the welfare effects of uncertainty under taxes or permits as in Stavins, because of the complexity of our solution above, we create a welfare differential metric similar to Weitzman and Newell and Pizer and simulate expected

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[****] Whereas Kim et al. (2006) consider the probability of arrival as another source of uncertainty, adding this to the uncertainty of dispersion is beyond the scope of the current research and is a fruitful topic for future research in this area. Further, another source of uncertainty is not likely to change our conclusions in a qualitative way.

values using numerical Monte Carlo techniques. Essentially, their "net benefit" measure compares the present value of the economic surplus generated from a first-best, socially optimal solution to that resulting from the regulated outcome under a location-specific tax regime and a location-specific system of tradable permits. The net benefit comparison in the current application is given by:

$$\Delta_{st} = E[NB_{st,tax}] - E[NB_{st,permit}], \qquad \textbf{(24)}$$

where E [ ] is the expectation operator, taken over the assumed distribution of uncertainty governing net dispersion.

In comparing welfare outcomes, we assume the output market is perfectly competitive, so all welfare effects are captured by producer's surplus. In this regard, the benefit function in each regime is given by the objective function described above – the maximum total surplus to society over the cost of producing cotton and controlling whitefly spread. Once optimal values for x and b are found, we substitute back into the specification for V^i to find the maximum welfare associated with the social solution, and each of the regulated firm solutions.

Empirical Model of Whitefly Diffusion and Optimal Control

The data used to estimate the diffusion equation is experimental *B. tabaci* data from field insecticide-trials conducted by ARS researchers (Naranjo, Chu and Henneberry, 1996; Naranjo et al., 1998) in Brawley, CA. These data represent two-years (each of 13 week durations) of insect counts, yield measurement, and whitefly control experimentation (see Richards, et al., 2009 for a detailed description). These data are summarized in table 1. Because the grid cells in the experimental plot were adjacent to each other in a 5x5 design, insects had the opportunity to move from cell to cell, and interact with insects in other locations as if each grid location was an individual farm. To simplify the spatial-dynamic model, we estimate the diffusion process for all 25 cells, but use the dispersion parameters from only the upper-left nine cells of the entire matrix. Although simplified, the estimation and optimization procedure is still very complex as the 3x3 structure consists of 81 distinct interaction parameters that must be estimated.

[table 1 in here]

With this data, and the objective of finding optimal control solutions across a set of geographically-contiguous locations, we parameterize each component of the optimal control model described above. We pool the data from each spatial location, *s*, over all 13 weeks, and both years, and estimate the equation of motion using a location-fixed effects procedure. Because observed control activities are endogenous, we estimate the constraint equation using a an instrumental variables procedure (2SLS) where the set of instruments includes the time of year, weather and lagged endogenous variables. The control variable, however, does not measure removals directly, but is a count variable that indicates the number of applications of a particular insecticide. Therefore, in the econometric model we estimate the apparent amount of control as a function of the number of insecticide applications, interactions between applications and population levels, cooling degree days (CDD), rainfall and a binary variable for the year 1994. Further, we define the change in insect population in discrete terms as the current population less that observed last period.

Note, however, that to obtain estimates of the growth parameter from Fisher's equation, we first need estimates of the dispersion coefficients that define the amount of population growth due to in-migration less out-migration. Consequently, we estimate the constraint equation using a two-step procedure, first estimating the dispersion coefficients using Fick's Law and non-linear least squares in a first step and then, using the estimates of d_{sj}, estimating the growth parameter, the location fixed-effects and parameters of the control function in a second stage. More formally, the estimation equation is given by:

$$b_{s,t} - b_{s,t-1} = r_s b_{s,t}(1 - b_{s,t}/K_s) + \sum_{j=1}^{S} d_{sj} b_{j,t} - x_{s,t}, \tag{25}$$

where d_{sj} are estimated using Fick's Law as:

$$\ln(b_{s,t}) = \ln(b_{s_0,t_0}) - (1/D)q^2/4t - \ln(2\sqrt{\pi D t}), \tag{26}$$

and the only parameter to be estimated is the rate of diffusion, D, from location j at distance q. In these data, the dispersion is smaller the further away from the origin, but the gap declines with time as insects are able to reach the further distances. Because control costs are determined by the marginal effect of control activities on insect numbers, the elements of $k()$ are estimated through equation (25) from the control function described above.

We then use the parameters estimated from (25) and (26) to populate the spatial-temporal optimal control model (all parameter definitions are summarized in table 2). Because insect movements are inherently random, the nine equations in nine unknowns are solved using Monte Carlo simulation with 1,000 draws from a standard normal distribution. Our primary interest lies in characterizing the steady-state solutions, so we calculate the solution for each location, and compare welfare results by summing over all nine grid locations. In the next section, we summarize these results, following the econometric model of whitefly dispersion.

[table 2 in here]

Results and Discussion

In this section, we present and discuss the econometric estimates of the spatial-temporal whitefly dispersion model, and the optimization results obtained from the optimal control procedure. Parametric estimates of the Fisher Equation model are presented first, and then the optimization results, beginning with the base-case scenario and then the comparative dynamic exercise used to test the core hypotheses of the paper, namely, the underlying conditions that influence the preference for taxes versus quotas in regulating insect dispersion externalities.

In temporal econometric models, the nature of time is well understood. However, in spatial models, or spatial-temporal models, it is important to understand the specific context of space under study. In table 3, we provide a description of the grid-structure of the experimental farm-community used in this study in terms of the distances between each cell. In table 4, we focus on the nine grid-locations that form the basis of the optimization model and show the dispersion rates, normalized across each row, between each pair of locations. From this table, it should be clear how the dimension of the problem expands with the complexity of the geography involved. These dispersion rates are calculated using the parametric estimates shown in table 5. The estimates in table 5, in turn, result from estimating Fisher's Equation and Fick's Law under the assumptions described above. Although we estimate this model using a location-fixed-effects procedure, we do not show the location effects here as there are a number of parameters in the full model.[*****]

Recall that control costs are inferred from the control function estimated as part of equation (25). The results in table 5 show that the control function is quadratic in the number of insecticide applications, and that the marginal effectiveness of control increases in the insect population, both as expected. Further, insect numbers fall with the number of cooling-degree days (warmer temperatures reduce population levels), but are unaffected by either rainfall or the yearly fixed effect. Using the assumption that marginal cost must equal marginal value in equilibrium, marginal control costs are calculated by multiplying the marginal product of control by the per-insect impact on gross margins (marginal yield times margin per pound by table 1). With the objective function and equations of motion thus parameterized, we then solve both the socially- and privately-optimal problems using Monte Carlo simulation.

[tables 3, 4, and 5 in here]

The optimal steady-state control and whitefly population values for each location are shown in table 6 below in the socially-optimal solution relative to the privately-optimal result. In each case, the difference between the privately and socially optimal solutions is considerable – on average the privately-optimal control amount is 24.02% larger than the socially-optimal amount and the population level 54.41% greater. Moreover, recall that the metric for infestation levels is number of adults per leaf, so aggregated to an entire field these values imply large absolute numbers of insects. Further, the difference in objective function values implied by these

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[*****] Because of the large number of cells in this, and any real-world application of this procedure, it was necessary to assume the movement parameters are constant across locations. This assumption could easily be relaxed with more detailed agronomic data on the conditions prevailing at each location.

differences is significant in an economic sense – the socially-optimal solution generates 8.32% more surplus than the private-optimal solution. However, relative to the number of adults in the sample data, both the privately and socially-optimal results show considerably lower infestation levels, suggesting that the market fails in some other important way that the model is not capturing. With these benchmark results, it remains to be seen which policy tool is able to restore the socially-optimal result in the most efficient way.

[table 6 in here]

To show the effect of using either policy tool on whitefly control strategies, we first consider the certainty case, where the policymaker is omniscient and is able to know exactly the amount of net dispersion from each cell to the others. In either case, however, it is a simple matter to design an optimal policy that restores the first-best result so this solution is of little interest. Under uncertainty, however, each of these tools is expected to generate different control paths, and different levels of aggregate welfare. These differences are of interest to policymakers and are shown in table 7. Based on 1,000 random draws for each dispersion coefficient, the expected present value cotton production is fully 45.8% higher under a quantity-based permit system relative to a price-based tax system. Further, a simple t-test of the difference in mean values between the two easily rejects the null hypothesis of equality at a 5% level. Clearly, therefore, permits are preferred in this case. This result, however, is exactly the opposite to that found by Hoel and Karp (2001, 2002) and Newell and Pizer and Karp and Zhang and supports Stavins' conclusions. In designing stock-externality control programs, policymakers need to understand the source of uncertainty – whether it derives from the demand side or the supply side and the correlation between the two – as much as they need to know that uncertainty matters.

[table 7 in here]

As in any policy-design problem, policymakers also need to know the parameters governing the slopes of the marginal social benefit and cost curves as welfare calculations are critically dependent upon them. In table 8, we show the effect of varying the slope of the marginal damage (marginal benefit) and marginal cost functions. In the upper panel, causing the slope of the damage function to rise from \$2.5 / insect to \$6.5 / insect causes the optimal value of cotton production, net of damage costs, to rise by 66.2% under a system of taxes, but to fall by 1.5% under a system of permits. Thus, steeper marginal social benefits favors taxes, and not permits. On the other hand, causing the slope of the marginal control-cost function to rise from \$0.05 / insect to \$0.15 / insect – a range that brackets the estimated value – causes the net benefit to rise by 84.3% under taxes, but 195.3% under permits. Therefore, steeper marginal costs favor a system of permits relative to taxes. Both of these results are, again, opposite to that found in the GHG regulation literature.

[table 8 in here]

This raises the obvious question, therefore, of which scenario is likely to prevail? Unlike the GHG literature, where the difference in social value between taxes and permits was found to be an order-of-magnitude different, the values in this case are sufficiently close, and sufficiently sensitive to variation in the key parameters, that extreme variation in one curve or the other could reverse our conclusions. However, in the case at hand, and in the neighborhood of infestation levels that growers will realistically allow to occur, an additional insect is not likely to increase the amount of damage over what has already been done. On the other hand, Q-biotype whitefly promise to be sufficiently difficult to kill that the incremental cost – perhaps an additional treatment per season – could be substantial.

Conclusions and Implications

The Q-biotype whitefly promises to be one of the most important invasive insect species to agriculture in the U.S. southwest, should it be allowed to spread. Government control efforts are not likely to be forthcoming, however, so this study investigates preferred institutional arrangements for addressing externality issues that prevent a system of private control from being fully efficient. Similar policy tools proposed for the control of GHG emissions find that a price-based system (taxes) is preferred to a quantity-based system (permits). However, these findings are based on the assumption that regulators are uncertain over the slope of the cost-of-control function, and that the benefits of control are irrelevant. If uncertainty arises on both sides of the equation, however, regulator preferences are likely to change to a quantity-based system of regulation. In the invasive species case, uncertainty is endemic to both the benefit and cost side as the growth and diffusion of insects from one farm to another are driven by biological processes.

We construct a spatial-temporal model of optimal insect control to investigate which policy tool is preferred. Under realistic parameter assumptions, and opposite to the conclusions of the GHG regulation literature, we find that a system of permits is preferred to a system of taxes. Moreover, we show that a steeper marginal social damage function favors the use of taxes, while a steeper control-cost function favors permits. Again, this result is opposite to previous results that assume only cost-based uncertainty. Based on the evidence provided by negotiations on climate change legislation in the U.S., this outcome is fortunate for insect regulators because permit-based systems of control are evidently more politically-acceptable than tax-based systems.

Our findings are likely to generalize beyond the invasive species case. Indeed, in the GHG regulation literature, uncertainty was assumed to lie on the cost side because it is highly plausible that regulators will not know the state of technology faced by polluters. However, given the unsettled science on this issue, uncertainty in the GHG case could just as easily come from mis-estimates of marginal social damage as well. Similar debates will arise in other forms of externality regulation, from water pollution to SO_2 control, even to the case of whether to force citizens to immunize themselves against influenza in the case of a threatened pandemic. In each of these cases, a similar analysis to that conducted here will have to be carried out.

As in the climate-change regulation case, however, there are many institutional details that would need to be resolved. Because the taxes and / or permits in our model are location-specific, the data-gathering effort required to implement any regulatory system would be difficult and costly. Nonetheless, most growers monitor insect infestations through either pheremone trap or sweep technologies anyway, so the burden of an additional requirement may be small. Advances monitoring technology, which would surely arise in the face of increased regulation, would likely reduce the cost of more intensive on-farm insect monitoring practices.

On the technology issue, future research in this area is necessary to investigate the relative incentives to develop innovative insect-control technologies if either a system of taxes or permits is put in place. Does a system of permits favor either chemical or biological control? Would growers instead have incentives to develop better management technologies in order to conserve permits? Are the assumptions used by Requate (1998) in answering these questions for the emissions case similarly critical to the invasive species example? Each of these questions is a potential avenue for future research.

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Table 1. B. tabaci Summary Data: Brawley, CA. Field Experiments

Variable[1]	N	Mean	Std. Dev.	Min.	Max
Treatment (#)	975	3.000	1.414	1.000	5.000
Eggs (#/cm^2)	975	6.830	11.270	0.030	104.540
Nymphs (#/cm^2)	975	1.486	2.715	0.000	25.970
Adults (#/leaf)	975	12.793	27.720	0.000	241.000
Temp. Max. (^{o}F)	975	100.720	10.470	73.000	115.000
Temp. Min. (^{o}F)	975	67.564	10.140	47.000	82.000
CDD (^{o}F)	975	19.538	9.642	0.000	34.000
Rain (in.)	975	0.002	0.016	0.000	0.100
CCDD (^{o}F)	975	1216.500	853.100	116.000	3017.000
CRain (in.)	975	1.644	0.294	1.300	1.960
Yield (kg/ha)	50	1553.000	394.220	660.000	2380.000

[1] Variables are as follows: Treatment is the number of insecticide applications per season, "Eggs" is the number of eggs per cm^2, "Nymphs" are immature insects per cm^2, "Adults" are adult insects per leaf, "Temp. Max." is maximum daily temperature in ^{o}F, "Temp. Min." is minimum daily temperature, CDD is cooling degree days (H - 65^{o}F), "Rain" is amount of rain received, in inches, on one day, "CCDD" is the cumulative number of CCDs over thesample period, and "CRain" is the cumulative rainfall over the sample period.

Table 2. Parameters Required for Whitefly Simulation Model

Variables:	**Units**	**Source**	**Value**
1. State Variable: b_{st}	# / leaf	Endogenous	
2. Control Variable: x_{st}	# / leaf	Endogenous	
3. Costate Variable: λ_{st}	$ / insect	Endogenous	
Parameters:			
1. K_s = carrying capacity	# / leaf	Estimate from MAC data	241.0
2. r_s = growth rate,	# / leaf	Estimate from MAC data	0.0823
3. d_{sj} = dispersal,	# / leaf	Estimate from MAC data	See below.
4. p_t = cotton price,	$ / kg.	AZ Ag. Statistics	$1.32 / kg.
5. c_{st} = marginal cost,	$ / kg.	U of A Farm Budgets	$0.70 / kg.
6. y_b = marginal damage	kg. / Ha.	AZ Ag. Statistics	4.656 kg / Ha
7. $k(b_{st}, x_{st})$ = control cost	$ / Ha.	Estimate from MAC data	
	$ / Ha.	k_x	\$37.37 + 0.101 b
	$ / Ha.	k_b	- \$1.73 + 0.101 x
	$ / Ha.	k_{bx}	$0.101 / Ha
8. δ = discount rate	%	Federal Reserve	0.05

Note: Marginal damage estimate taken from Richards, et al. (2006). Infestation intensity is commonly measured using sampling methods on a per-leaf basis. Control cost function estimated in yield units (kg / Ha) and multiplied by the assumed grower margin.

Table 3. Distances Between Cells of Experimental Plot, in Index Measure

		Cell Column Address				
		1	2	3	4	5
Cell Row Address	1	0.000	0.100	0.200	0.300	0.400
	2	0.143	0.000	0.143	0.286	0.429
	3	0.333	0.167	0.000	0.167	0.333
	4	0.429	0.286	0.143	0.000	0.143
	5	0.400	0.300	0.200	0.100	0.000

Table 4. Normalized Dispersion Rates after Imposing Adding-Up Condition

(Row, Col)	**(1, 1)**	**(1, 2)**	**(1, 3)**	**(2, 1)**	**(2, 2)**	**(2, 3)**	**(3, 1)**	**(3, 2)**	**(3, 3)**
(1, 1)	0.000	1.444	0.780	1.444	1.169	0.623	0.780	0.623	0.229
(1, 2)	1.143	0.000	1.143	0.868	1.143	0.868	0.322	0.479	0.322
(1, 3)	0.376	1.041	0.000	0.219	0.765	1.041	-0.174	0.219	0.376
(2, 1)	1.143	0.868	0.322	0.000	1.143	0.479	1.143	0.868	0.322
(2, 2)	0.536	0.811	0.536	0.811	0.000	0.811	0.536	0.811	0.536
(2, 3)	-0.123	0.423	0.698	0.034	0.698	0.000	-0.123	0.423	0.698
(3, 1)	0.376	0.219	-0.174	1.041	0.765	0.219	0.000	1.041	0.376
(3, 2)	-0.123	0.034	-0.123	0.423	0.698	0.423	0.698	0.000	0.698
(3, 3)	-0.634	-0.240	-0.083	-0.240	0.306	0.581	-0.083	0.581	0.000

Note: Own-dispersion is not defined in this model. The nine cells represented here are drawn from a larger 25 x 25 matrix of dispersion rates throughout the entire sample plot.

Table 5. Estimates of Whitefly Diffusion Model: Fisher's Equation / Fick's Law

First-Stage Estimates of Diffusion Parameters

Parameter	Definition	Estimate	t-ratio
D	Diffusion Rate	166.281*	9.034
LLF		-2,134.553	

Second-Stage Estimate of Growth Model Parameters

Parameter		Estimate	t-ratio
r	Growth Rate	0.087*	6.518
b_{st}	Population	13.347*	3.948
$b_{st}q_{st}$	Population*Distance	-0.664	-0.549
x_{st}	Control Level	2.239	1.859
$b_{st}x_{st}$	Population*Control	0.211*	11.096
x_{st}^2	Control^2	-0.673*	-2.876
CDD	Cooling Degree Days	-0.305*	-4.039
$RAIN$	Rainfall	44.975	1.189
$D94$	1994 Binary	1.759	1.442
LLF		-4,031.347	

Note: Estimates in this table obtained with the ARS experimental data using a two-stage procedure. Plot-specific effects in the growth model are available from the authors. Significance at a 5.0% level is indicated by a single asterisk.

Table 6. Steady-State Solution to Spatial-Temporal Control Problem: Socially versus Privately Optimal Control and Population Levels: Baseline Assumptions

	Social Optimal		Private Optimal	
Location (Row, Col)	**Control Level**	**Population**	**Control Level**	**Population**
(1, 1)	4.000	6.687	4.960	10.095
(1, 2)	3.876	6.366	4.800	9.759
(1, 3)	3.420	5.814	4.240	8.900
(2, 1)	3.875	6.363	4.799	9.757
(2, 2)	3.694	6.005	4.575	9.371
(2, 3)	3.045	5.382	3.784	8.381
(3, 1)	3.381	5.779	4.200	8.863
(3, 2)	3.042	5.378	3.782	8.377
(3, 3)	0.862	4.247	1.599	6.820
Objective Function:	$69,674.391		$64,321.862	

Note: Solutions are means of Monte Carlo simulation with 1,000 draws from normal distribution under base-case parameter assumptions. Optimal population and control levels are measured in adult insects per leaf.

Table 7. Comparison of Welfare Under Taxes vs Permits: Baseline Assumptions

	V_0	σ_V	Min.	Max.	t-ratio
Tax	688.330	110.960	387.920	958.750	-40.957
Permits	1,003.700	201.780	608.440	1,399.400	

Note: Solutions are means of Monte Carlo simulation with 1,000 draws from normal distribution under base-case parameter assumptions.

Table 8. Comparative Dynamics: Effect of Marginal Damage / Marginal Cost Variation

	Taxes		Permits		
y_b	V_0	σ_V	V_0	σ_V	t-ratio
2.500	527.060	55.640	1,532.200	533.420	
3.500	634.580	71.420	1,533.600	531.170	
4.656	*742.380*	*89.451*	*1,524.900*	*478.570*	
5.500	809.530	102.530	1,510.700	440.180	
6.500	876.010	118.060	1,483.800	396.410	
k_x	V_0	σ_V	V_0	σ_V	t-ratio
0.050	533.000	71.672	913.490	280.580	
0.075	636.200	79.920	1,151.300	358.270	
0.101	*742.380*	*89.451*	*1,524.900*	*478.570*	
0.125	855.170	96.269	2,016.300	639.640	
0.150	982.360	100.940	2,697.700	865.820	

Note: Solutions are means of Monte Carlo simulation with 1,000 draws from normal distribution. Base-case parameter assumptions are in italics.