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Technology Adoption Against Invasive Species

Ram Ranjan

This article looks at technology adoption in agriculture that is specifically targeted against invasive species. The analysis involves predicting the long-term distribution of technology choices when technology can be adopted and disadopted based on current and expected agricultural profits influenced by pest infestation. The theoretical analysis is based on an extension of two authors' findings in 1993 and incorporates the possibility that psychological factors, such as complacency, have a significant impact on technology adoption and hence disease establishment. An empirical application is performed for soybean rust.

Key Words: adoption psychology, invasive species, popularity weighting, soybean rust, technology adoption

JEL Classifications: Q16

Several features differentiate technology adoption specifically targeted against invasive species from the conventional pattern of technology adoption in agriculture. First, the adoption and disadoption of technology may be correlated with the pest population. A reduction or elimination of the pest population may lead to the disadoption of that technology. Second, technology itself may continue to change faster than the rate of adoption because of the need to incorporate measures such as resistance and control of multiple pests, consumer reaction, and productivity effects.[1] Finally, technology adoption in conventional agriculture is geared toward attaining higher profitability, whereas the immediate aim of technology adoption against invasives is mostly preventive and therefore is subject to fluctuations borne out by the adopter's psychological responses, such as complacencies or compulsions.

Technology adoption is significantly influenced by learning by doing or by observation, as argued in the literature. However, in the adoption of a new technology, to ward off a threat from invasive species, complacency may play a crucial role in determining its extent of adoption and consequently decide the eventual establishment of the pest. Geoffard and Philipson point out that the vaccination demand for diseases such as tuberculosis and influenza falls as the prevalence of the disease in the population falls. This phenomenon, characterized as the prevalence effect, may also be found in invasive species that threaten agriculture. Farmers whose crops have not yet been infected with invasive species might wait until the pest arrives as close as the neighbor's farm. This complacency may also be aggravated by the presence of government indemnity programs and insurance schemes. Empirical work on measuring or explaining the extent of complacency effects is missing from invasive species research but exists in several other fields. Sterman and

Ram Ranjan is an economist with CSIRO/Land and Water, Wembley, Australia.

[1] For instance, the ability to include productivity-enhancing genes along with pest-resistant features in soybean requires a larger genetic pool. Other desirable features may include those that enhance its consumer desirability, such as low-saturated fatty acids and higher protein contents. Resistance to abiotic forces is also a desirable feature, as it enhances productivity.

Booth Sweeny (2005) argue that one reason people do not show any sense of urgency when it comes to global warming is due to their "difficulty to relate flows in and out of stock to the trajectory of stock." Consequently, the stock of carbon is understood to be falling with the reduction of emissions, even as the net inflow into the stock may be positive. This behavior is known as pattern matching heuristics (Sterman and Booth Sweeny 2002). Complacency against infectious diseases may have similar origins; people relate a reduction in pest infestation rate to a reduction in the total infested population. No matter what the basis for complacency, the fact of its existence cannot be overlooked.

In opposition to the complacency effect, certain factors, such as the influence of a neighbor's actions on one's own profitability, might compel technology adoption. For instance, precision application of fungicides to soybean rust in a certain location reduces the risks in the applied areas but significantly increases the risk of infestation in the neighborhoods where such applications have not been made. This may have a positive cascading impact on technology adoptions. Whether or not forces influencing technology adoption are of the "complacency type" or the "compelling type" would depend on pest characteristics, its modes of transport, and several other regional, social, and behavioral factors.

In this article, I look at the issue of technology adoption in agriculture that is directed toward combating invasive species. I build on the previous literature on technology adoption that highlights the role of adaptive learning in the process of technology adoption (Ellison and Fudenberg 1993, 1995). The role of public communication, such as mass media, and interpersonal communication, such as between neighboring farmers, input suppliers, and regulatory agents, has been crucial in determining the spread and adoption of new technologies in agriculture. Although mass media creates awareness, interpersonal communication is more crucial in transferring technical knowledge to farmers (Longo).

The analysis in this article examines the long-term distribution of technology choices when technology can be adopted and disadopted based on current and expected profits in agriculture. The approach involves extending the Ellison and Fudenberg (1993) model of technology adoption through learning from neighbors. In doing this, agents discard historical information and assign a popularity weighting to the objective information that is available in each period in the form of profit differential between the existing and the available technology. This weighting may lead to full convergence, even when the difference in the two technologies is a random event. In this article, I explore the role of psychological factors, such as complacency from risk reduction, in adding an additional element toward influencing technology adoption behavior. The impact of adaptive learning on the adoption of technology is analyzed given a complacency effect from a reduction in risks or a compulsion effect from adoption of technology in wake of the reduced expected profitability from not doing so. The theoretical analysis confirms the intuition that psychological factors such as complacency have a significant impact on technology adoption and hence disease establishment. Further, learning from neighbors may not necessarily lead to higher technology adoption. In fact, overall adoption may go down based on the level of complacency.

An empirical analysis is also performed for the recent soybean rust advent into the United States.[2] Even though the pest is already present in the United States, the infestation rates so far have been fairly low. However, a significant threat exists of future severe infestations if adequate preventive measures are not taken. This threat is further com-

[2] In terms of soybean yield differences among farmers, technology adoption has been believed to be a deciding factor. Those farmers who are able to exploit better technology can produce soybeans at a cost of $2bu/acre, compared with $10bu/acre for those who do not (Wherspann). In general, the rate of technology adoption has been found to be quite significant in agriculture in certain areas. Fernandez-Cornejo and McBride found that the adoption of herbicide-tolerant soybeans rose from 17% in 1997 to about 81% in 2003 for the United States.

pounded by extreme weather events, such as hurricanes, that are capable of transferring soybean spores to distant areas. Because of the spatial and temporal differences in soybean rust infestation within the various soybean-growing regions of the United States, there is significant scope for learning from infestations and treatment results within the neighboring states. Consequently, psychological perceptions may play a role in disease spread in the short run. The long-term spread and establishment of the disease may be determined by the nature and speed of the learning process for the farmer over the pest's optimal management strategy.

In the following sections, I look at a model of technology adoption and derive extensions that are unique to invasive species.

Model

Let there be two technologies, an existing one (f) and an alternative one (g) that is supposed to be more effective against invasive species. Technology g could be thought of as a pest-resistant variety of crop that is available to the farmer or a better management practice involving timely fungicide applications. I assume that both the existing and alternative technologies are optimal choices for farmers and that each farmer receives the same benefits from their use. The difference in the payoffs between these two technologies is given by $U^g - U^f \geq \theta + \varepsilon$, where U^g is the utility from the alternative technology, and U^f is the utility from the existing technology. The deterministic component of payoff differential is θ, and the stochastic component with a uniform distribution is ε. Following the mathematical approach of Ellison and Fudenberg (1993), I assume that farmers' decisions to adopt technology g are based on a popularity weighting scheme that influences their decision to switch. This scheme is given by $m(1 - 2x)$, where m is the popularity weight assigned to the proportion of farmers (x) who have already adopted the better technology. The farmers' decision problem is then to choose g if $U^g - U^f \geq m(1 - 2x_t)$. Notice that under this kind of selection scheme, the more popular technology will be selected, even if the current payoff from that technology is low. This is evident by substituting values of 0.5 or more for x in the above equation, which turns the right-hand-side negative.

I incorporate the complacency effect by initially assuming that complacency sets in with an increase in the proportion of farmers adopting the better technology. This kind of assumption is justified when an increase in the level of adoption has a negative influence on the rate of infestation, thus reducing the risk of further spread. When this happens, a marginal increase in the adoption of technology would require a higher differential in payoffs between the two technologies, as the farmer is now reluctant to switch to the better technology if the threat is reduced. This possibility would lead to switching when $U^g - U^f \geq m(1 - 2x_t) - q(1 - kx_t)$, where q is the parameter that influences the level of complacency, and k determines the proportion of adopted population beyond which complacency sets in. Following the analysis of Ellison and Fudenberg (1993), I derive the dynamics of agricultural technology adoption and conditions for full technology adoption. Ellison and Fudenberg (1993) assume that in each period, due to inertia, only a fraction of the population, given by α, is able to make the choice of whether or not to switch. In the case of an invasive species, this can be thought of as a spatial parameter that may relate to the proximity of the population that is up for choice, to the population that has already adopted the better technology. I do not specifically model farmer heterogeneity but assume that the inertia reflected in technology adoption is caused by this heterogeneity. However, farmer heterogeneity could also play an important role in determining the extent of technology adoption (Fernandez-Cornejo and McBride). The population that adopts the technology is then given by the following rule:

$$(1) \quad x_{t+1} = x_t + \alpha(1 - x_t) \text{ with probability } P[1 - H(m(1 - 2x_t) - q(1 - kx_t) - \theta)],$$

where H is the cumulative distribution function of the random term ε, which is uniformly distributed on the interval $[-\sigma, \sigma]$, and σ is the range of the random event. Growth in x is determined by the probability that the random element of the profit, ε, is at least larger than the popularity and complacency weighted deterministic element of profit θ. Similarly, the conditions for a downward movement in x are given by

(2) $x_{t+1} = (1-\alpha)x_t$ with probability $P[H(m(1-2x_t) - q(1-kx_t) - \theta)]$.

Following Ellison and Fudenberg (1993), the level of x, say x^g, beyond which the better technology is certain to be adopted, is given by

(3) $\theta + \varepsilon \geq (m(1-2x_t) - q(1-kx_t))$,

which can be derived by noting that x_t is certain to move forward if the minimum value of payoff is positive. This is possible when $\varepsilon = -\sigma$:

(4) $$x(t) \geq x^g \equiv \theta - \sigma \geq m(1-2x_t) - q(1-kx_t).$$

This gives

(5) $$x^g \geq \frac{\sigma + m - q - \theta}{2m - qk}.$$

Similarly, the value of x, say x^f, below which a backward step takes place with certainty, is derived as

(6) $$x_t \leq x^f \equiv \theta + \sigma \leq m(1-2x_t) - q(1-kx_t),$$

which gives

(7) $$x^f \leq \frac{(-\sigma + m - q - \theta)}{2m - qk}.$$

Also, realizing that the minimum probability of an upward step is possible when $x = 0$, I get this probability as

(8) $P(\theta + \varepsilon \geq m - q)$,

or,

(9) $$P[\theta + \varepsilon \geq m - q] = \frac{\sigma - m + q + \theta}{2\sigma} = \frac{-x^f(2m - qk)}{2\sigma}.$$

Similarly, the minimum probability of a downward step is realized when $x = 1$:

(10) $P(\theta + \varepsilon \leq -m - q + qk)$,

or,

(11) $$P[\theta + \varepsilon \leq -m - q + qk] = \frac{\sigma - m + qk - q - \theta}{2\sigma} = \frac{(x^g - 1)(2m - qk)}{2\sigma}.$$

From above, Ellison and Fudenberg derive the conditions for convergence of the technology as

(12) $x^g < 1, \quad x^f < 0 \geq x_t \to 1.$

(13) $x^g > 1, \quad x^f > 0 \geq x_t \to 0.$

(14) $x^g > 1, \quad x^f < 0 \geq$ no convergence.

(15) $x^g < 1, \quad x^f > 0,$ if $x_0 > x^g \geq x_t = 1$; however, if $x_0 < x^f \geq x_t = 0$.

Equation (12) implies that the better technology will eventually be adopted if $x^g < 1, x^f < 0$. Also note that when $m - q = \sigma$ and $q < 2$, $x^g < [2(m - q) - \theta]/(2m - qk) < 1$, and $x^f = (-\sigma + m - q - \theta)/(2m - qk) < 0$. Therefore, when the popularity weighting impact net of any complacency impact equals the maximum range of the random error, the entire population converges toward the better technology. Ellison and Fudenberg characterize this as the optimal weighting scheme as convergence happens with probability 1. Similarly, when the popularity weighting impact net of any complacency impact either exceeds or is less than the maximum range (σ) of random error, convergence is possible, depending on the starting point.

Now, let's derive the conditions for convergence when the complacency effect dominates popularity weighting. Specifically, the condition for a forward step with certainty is $\theta - \sigma \geq m(1 - 2x_t) - q(1 - kx_t)$. Because, in this case, $q > m$, the lower the value of x, the higher the probability of a forward jump. Therefore, a forward jump happens with certainty when $x \leq x^g \equiv (-\sigma - m + k + \theta)/(-2m + qk)$. Similarly, a backward jump happens with certainty when $x \geq x^f \equiv (\sigma - m + k + \theta)/(-2m + qk)$.

It is obvious that the better technology will not be adopted with certainty, thus leading to less than full convergence in the long run. Notice that, as x increases, the probability of an upward step keeps decreasing. It can be shown that the system will converge toward the conventional technology with positive probability if $x^g < 0$.

While the above setting assumes a linear relation between the popularity and complacency effect, thus allowing the stronger effect to dominate, the complacency effect may also be nonlinear in the level of adoption. For instance, low levels of adoption might also reflect low threat from disease, thus making would-be adopters in a neighboring region complacent. Similarly, high levels of adoption could imply a low level of disease, too, due to the impact of higher adoption, again discouraging remaining would-be adopters, whereas in the middle, the complacency effect could be low, as would-be adopters see a significant threat from the pest. Such a relationship, however, is entirely governed by how pest infestation is influenced by technology adoption.

Some Extensions

Now, let me discuss some of the features that are unique to the agricultural technology associated with invasive species. One possibility is that the benefits from the better technology keep increasing with adoption as the pest population gets under control. Another possibility is exactly the opposite—that of a falling differential in profits with increasing adoption. There are several reasons why this may happen, and I discuss that in the ensuing sections. Finally, nonlinearity in the profit differential is taken up.

Increasing Payoff Differential

The payoff differential may be increasing with the adoption of the new technology if the impact of the pest is increasing in proportion to the population by the better technology. This is a plausible scenario, as the host size for the invasive species reduces, thereby concentrating the existing pest population on the remaining areas that use the older technology. Such a payoff differential can be thought of as being dependent on the proportion that uses the new technology as $\partial(U^g - U^f)/\partial x_t > 0$. Payoff differential may also be increasing because of quality or reputation effect. In certain cases, the new technology may also end up adversely affecting other pests of the commodity, thus increasing productivity (Livingston et al.).

Declining Payoff Differential

Difference in payoffs could also be falling with adoption because of several reasons. First, the impact of the invasive pest may fall with the level of adoption, making it impossible for the pest to establish once the host population (given by the percentage of population that uses the old technology) falls below a certain threshold. Initial adopters may be compensated for the high costs of production by the higher rewards from possible enhanced productivity. However, as the proportion of adopters of new technology increases, increased productivity might bring the profits down, thus making the new technology costlier. Note that this situation may also be highly conducive for complacent behavior, as a reduction in the difference in profits caused by reduced damages from pests discourages adoption of new technology. Second, profits may fall if the preferences for the old variety (by old technology) increase because of consumer skepticism and reluctance to try new varieties. Profits may also fall from an increased supply of the agricultural commodity in the market caused by the new technology. If the demand for the agricultural commodity is highly elastic, this might cause a reduction in overall profits for everyone. Profits may decrease if the supply of new technology or the inputs needed by it are scarce. There may also be behavioral resistance to further adoption, as new technology may require additional efforts to help prevent pests from becoming resistant to it. Finally, heterogeneity in the population given by differences in production costs would lead to

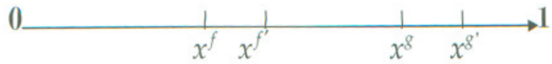

Figure 1. Shift in Certainty Cutoffs due to Declining Differential in Profits

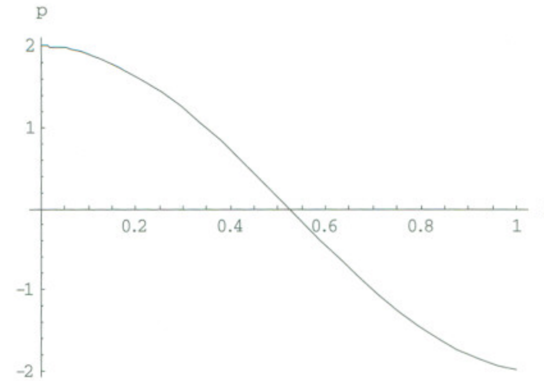

Figure 2. Profit Differential with a Change in the Level of Adoption

farmers with higher costs postponing their adoption until later on. When this happens, there may be a threshold level of population for technology adoption, beyond which it is optimal for the farmers who still use the conventional technology not to adopt. Declining payoff differential could be mathematically represented as $\partial(U^g - U^f)/\partial x_t < 0$.

Consider the possibility that the payoff differential is decreasing with adoption, as given by $\theta(1 - x_t)$. A farmer would choose the better technology if $\theta(1 - x) + \varepsilon \geq m(1 - 2x_t)$. Now, the value of x beyond which a forward step is possible with certainty is given by $x_t \geq x^{g^*} \equiv (\sigma + m - \theta)/(2m - \theta)$. The value of x_t below which a backward step is possible with certainty is given by $x_t \leq x^{f^*} \equiv (-\sigma + m - \theta)/(2m - \theta)$. When the payoff differential remains constant and equal to θ, the same cutoffs are given as $x_t \geq x^{g^*} \equiv (\sigma + m - \theta)/2m$ and $x_t \leq x^{f^*} \equiv (-\sigma + m - \theta)/2m$. Consequently, a falling differential shifts the cutoffs toward the right, as shown in Figure 1. Intuitively, it becomes much easier for the system to move toward the conventional technology and away from the better one.

Nonlinear Payoff Differential

Nonlinearity in adoption may arise from several reasons. First, if the new technology is a biologically altered plant variety that may be resistant to pests or herbicides, its profitability may depend on several key factors, such as public preferences for the new food and overall market size. A small market for a new variety of plant may soon get glutted with output, thus lowering prices and possibly profits. In this case, the difference in profits between the old and new technologies may turn from positive to negative as the adoption level for the new technology increases. Consider consumer preferences for genetically modified and organic foods. As the level of genetic alteration increases in the new variety of plants, consumers' skepticism may increase too, thus making the traditional plant variety more preferable. If the supply of the traditional variety falls from a lower population producing it, the prices may increase, thus making the lower technology more profitable. This nonlinearity can be incorporated by assuming that the payoff function is nonlinear and given by $\theta \cos(3x_t)$. Figure 2 shows the profit differential as the level of adoption increases from 0 to 1.

Next, I plot the conditions that ensure certainty of forward and backward motions. For a given set of parameters, $\theta = 2$, $\sigma = 4$, $k = 2$, and $m = 2$, certainty of an upward movement is given by the condition that $\theta \cos[3x_t] - m(1 - 2x_t) - \sigma > 0$. The condition for certainty of a backward step is given by $\theta \cos[3x_t] - m(1 - 2x_t) + \sigma < 0$. This is shown in Figures 3 and 4.

As evident from the two figures above, neither forward nor backward steps are possible with certainty for any value of x, which should be obvious, given the nonlinearity in the profit function and the ensuing disincentive to adopt marginally at high stages of adoption and to disadopt marginally at low stages of overall adoption. Now, let me consider the long-term distribution of the system.

The fraction of people who have adopted can take the following possible steps: $x_t = 0$, ¼, ½, ¾, and 1. The probabilities of forward

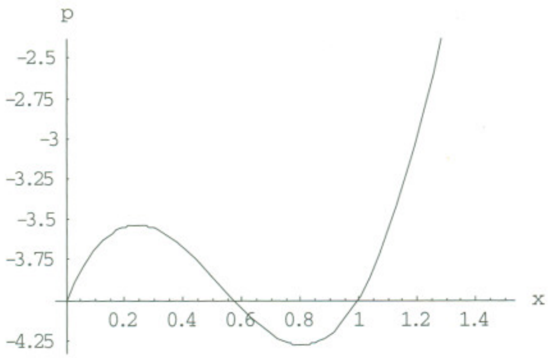

Figure 3. Certainty of a Forward Movement Note: The certainty of a forward movement is given by $\theta \cos[3x_t] - m(1 - 2x_t) - \sigma > 0$. Because there are no positive values for any given level of x, the condition for full convergence does not exist.

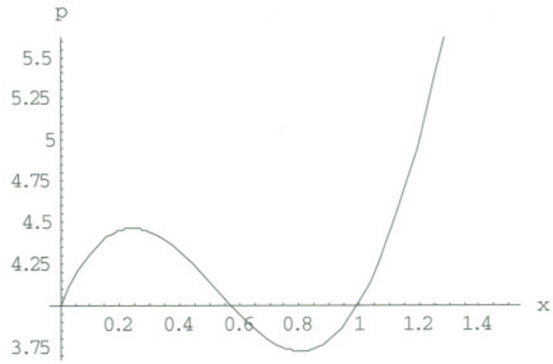

Figure 4. Certainty of a Backward Movement Note: The certainty of a backward movement is given by $\theta \cos[3x_t] - m(1 - 2x_t) + \sigma < 0$. Because there are no negative values for any given level of x, the condition for full convergence does not exist.

and backward steps are given by

$$(15)\quad \text{pr}(\{x_{t+1} \mid x_t\}) = \text{pr}(\theta\cos(3(x_t))) + \varepsilon \geq (m(1 - 2x_t) - q(1 - kx_t))) = \frac{\sigma - m(1 - 2x_t) + q(1 - kx_t) + \theta\cos(3x_t)}{2\sigma}.$$

$$(16)\quad \text{pr}(\{x_{(t+1)} \mid x_{(t)}\}) = \text{pr}(\theta\cos(3x_t)) + \varepsilon \leq (m(1 - 2x_t) - q(1 - kx_t))) = 1 - \frac{\sigma - m(1 - 2x_t) + q(1 - kx_t) + \theta\cos(3x_t)}{2\sigma}.$$

For $m = 2$, $\sigma = 5$, $\theta = 2$, $q = 0$, and $k = 0$, the probabilities of transition between states are given as $\{p(0, 1/4), p(1/4, 1/2), p(1/2, 3/4), p(3/4, 1)$, and $p(1, 1)\} = \{0.5, 0.55, 0.6, 0.65$, and $0.7\}$, where $p(0, 1/4)$ is defined as $\text{pr}(\{x_t = 1/4 | x_t = 0\})$ and is given by the first row, first column element of the probability transition matrix in Table 1.

The long-run fraction of time spent in each of the states is given by $\{P(0), P(1/4), P(1/2), P(3/4)$, and $P(1)\} = \{0.18, 0.19, 0.22, 0.21$, and $0.2\}$, where $P(0)$ is the long-term fraction of time spent in state $x(0)$. The long-term fraction of time spent in each of the possible states is calculated by raising the matrix to a power n, where n is any large integer that ensures a convergence of probabilities. As evident from the above data, all states are equally attractive in the long run. Note that the variance parameter σ plays an important role in determining the convergence of the adoption process. A higher variance would push the values of x_t toward the extremes (toward 0 or 1) for which a backward or a forward movement is possible with certainty.

Technology Adoption and Disease Establishment

Heterogeneity in the population can be present for several reasons, such as differences in production and treatment costs and differences in the age, education, and risk perception of the population. However, spatial heterogeneity may be another key factor having a significant impact on the level of adoption. So far, in the above sections, I have concentrated on the level of technology adoption without paying any attention to how it might have an impact on disease spread and establishment. It is obvious that less than full adoption may have a bearing on the long-term impact of the disease, and there were several cases above where the better technology could not be adopted with probability 1. In this section, I explore the impact of less than full adoption on disease establishment when there is spatial heterogeneity.

Consider the threat of infestation that affects two regions: x and y. Region x is the follower, whereas region y is the one affected first. Region x demonstrates complacency in

Table 1. Transition Probability Matrix

	$x_t = 0$	$x_t = 1/4$	$x_t = 1/2$	$x_t = 3/4$	$x_t = 1$
$x_t = 0$	0.5	0.5	0	0	0
$x_t = 1/4$	0.46	0	0.54	0	0
$x_t = 1/2$	0	0.49	0	0.51	0
$x_t = 3/4$	0	0	0.53	0	0.47
$x_t = 1$	0	0	0	0.5	0.5

adoption, which is given by $\theta + \varepsilon \geq m(1 - 2x_t) - q(1 - 2y_t)$. This complacency in adoption is not only based on adoption within region x, but is also influenced by the level of adoption in region y, as given by the parameter q. Notice that, as the level of technology adoption within region y increases, the threshold for adoption within region x falls at first, but once the level of adoption crosses half, the threshold level of adoption within x starts increasing in y. This captures the complacency that may set in from a temporary reduction in pest threats due to a higher level of adoption in the frontier region y. Region y has the standard response as $\theta + \varepsilon \geq m(1 - 2y_t)$. Probability of a forward step for region x is given by

$$(17)\quad P[\theta + \varepsilon \geq m(1 - 2x_t) - q(1 - 2y_t)] = \frac{\sigma - m(1 - 2x_t) + q(1 - 2y) + \theta}{2\sigma}.$$

Probability of a forward step for region y is given by

$$(18)\quad P[\theta + \varepsilon \geq m(1 - 2y_t)] = \frac{\sigma - m(1 - 2y_t) + \theta}{2\sigma}.$$

Now, to look at the steady-state distribution of the system, I divide the state space into nine parts as follows:

$$(19)\quad \{x0y0, x0y0.5, x0y, x0.5y0, x0.5y0.5, x0.5y, xy0, xy0.5, xy\}.$$

The transition matrix representing the probability of transition between these nine states is shown in the Appendix. For parameter values $\sigma = 5, \theta = 2, m = 2$, and $q = 1$, the steady-state distribution in these nine states is given as row 1 of Table 2.

Notice that the system has a high propensity to settle in the state when both the regions adopt the technology. Now consider a higher complacency effect in region x from adoption in region y. This is given by parameters $\sigma = 5$, $\theta = 2$, $m = 2$, and $q = 4$; the steady-state distribution is now given as row 2 of Table 2. Notice that the propensity of the system to spend time in the last state when x and y have fully adopted has fallen drastically. Consider now a scenario where profits are influenced by the level of adoption. More specifically, profits increase as the level of adoption increases in both the regions. I define parameters $t1 \ldots t9$ that replace θ depending on the level of adoption in the two regions combined. The new set of parameters is $\sigma = 5$; $\theta = 2$; $m = 2$; $q = 1$; $t1 = 0$; $t2 = 0.5$; $t3 = 1$; $t4 = 0.5$; $t5 = 1$; $t6 = 1.5$; $t7 = 1$; $t8 = 1.5$; and $t9 = 2$.

The steady-state distribution (say for the base case) is now defined as row 3 of Table 2. Obviously, an increase in profitability from adoption provides added incentive to adopt, as evident from the new steady-state distribution. When profits are falling in adoption, which could happen because of an increase in

Table 2. Steady-State Distribution in the Nine Possible States

	x0y0	x0y0.5	x0y	x0.5y0	x0.5y0.5	x0.5y	xy0	xy0.5	xy
Row 1	0.0059	0.0166	0.1426	0.0067	0.0178	0.1557	0.0570	0.0818	0.5155
Row 2	0.0097	0.0592	0.5546	0.0067	0.0083	0.1315	0.0531	0.0486	0.1277
Row 3	0.0384	0.0409	0.1581	0.0270	0.0259	0.1273	0.0915	0.0822	0.4083
Row 4	0.0316	0.0589	0.2063	0.0414	0.0517	0.1388	0.1523	0.1201	0.1984

productivity from a better technology adoption, there may be an incentive not to adopt. For the parameters $\sigma = 5$, $\theta = 2$, $m = 2$, $q = 1$, $t1 = 2$, $t2 = 1.5$, $t3 = 1$, $t4 = 1.5$, $t5 = 1$, $t6 = 0.5$, $t7 = 1$, $t8 = 0.5$, and $t9 = 0$, the steady-state distribution is given as row 4 of Table 2. Another interesting exercise would be to consider the impact of a higher adoption in region y on profits in region x and the subsequent impact on the long-term distribution. A higher adoption in region y may lead to an increase in productivity, thus reducing profits in case the demand for the good is inelastic. This may have an adverse impact on adoption in region x for parameters $\sigma = 5$; $\theta = 2$; $m = 2$; $q = 1$; $t1 = 0$; $t2 = 0.5$; $t3 = 1$; $t4 = 0.5$; $t5 = 1$; $t6 = 1.5$; $t7 = 1$; $t8 = 1.5$; and $t9 = 2$.

Consider a positive impact on region y's profits from technology adoption but no impact on region x's profits. That is, the values of $t1$ ... $t9$ are all zeros for region x, whereas they are as given above for region y. It can be verified that the proportion of time spent in states when region x is fully adopted falls almost to half, and the proportion of time spent in states when it is fully disadopted doubles from the base case.

Application to Soybean Rust

Soybean rust, a disease of the soybean and several other plant species, has been threatening the U.S. soybean crop since it arrived in 2004. Although the threat was reduced in the subsequent years because of limited infestations during the crop season, the potential for the pest becoming endemic is serious and calls for long-term planning to manage this pest. Soybean rust is chiefly windborne and is capable of transcontinental migrations helped by favorable events such as hurricanes. In fact, hurricane Ivan of 2004 is suspected as the medium for bringing soybean rust from South America. Soybean rust could cause significant damages to the U.S. soybean crops, and available estimates in the literature project losses of up to U.S. $2 billion/y from the disease (USDA-ERS).

Management of soybean rust would require significant private participation involving soybean-growing farmers in the United States in order to monitor and control its yearly migration across regions. Because of its ability to survive in cool and wet climates, it is possible for the rust to overwinter in the southern states and infest soybean crops during the growing season. Kudzu, a secondary host of the rust, is predominantly found in the southern states and could greatly assist in the long-term establishment of this pest. Management of soybean rust would require understanding the cropping decisions of the farmers and being able to influence decisions through public policies. Crop rotations, such as switching between soybeans and corn, and adequate precautionary steps, such as spraying of plants with fungicides, could significantly diminish the damages from soybean rust. Yet crop rotations are a function of several economic criteria, such as differential economic yield between various crops per acre, yield drags and additional input costs involved in suboptimum crop rotations, and the risk perception of the farmers. Similarly, decisions over how much or whether or not to spray are influenced by risk perceptions and could vary from location to location based on farmer and regional heterogeneity. Adaptive management of crops faced with threat of invasion can be expedited by public polices that reward socially optimum practices. For this to be possible, an understanding of farmers' learning capabilities under various infestation scenarios is crucial, as it would help policy makers be prepared in terms of public inducement programs.

Here, I select two regions, the Mississippi Delta and the U.S. Heartland, for analysis. Total average profits ($/acre) for the years 2003 and 2004 in the two regions, net of operating costs, are presented in the Tables 3 and 4. These figures have been estimated with U.S. Department of Agriculture National Agricultural Statistics Service data (USDA-NASS).

The range of profits in the various scenarios of infestation, no infestation, treatment, and no treatment is calculated and assigned a uniform distribution. Consequently, it is assumed that the probability of adoption is

Table 3. Adoption Data for Mississippi

Mississippi	Treat	No Treat	Difference
Not infested (profits—\$/acre)	165.93	190.93	−25
Infested (profits—\$/acre)	157.51	0	157.51
Range of difference \$/acre			182.51
F(d)~U	0.005479		
P(adoption)	0.863028		
P(disadoption)	0.136972		

positive whenever the profits are in the non-negative range. For simplicity, I assume that currently there are no complacency effects. Next, I look at the adoption of treatment technology for the region of Mississippi. When adoption inertia is low, state space is defined as the fraction of population that has adopted the spraying technology in any given time period. Let $0 < x_t < 1$ be the fraction of people who have adopted the new technology at time t. There is inertia in the system, as a result of which only a fraction of the population can adopt or reject the new technology per unit of time. More specifically, the fraction of people using the new technology can take the following possible steps:

$$x_t = 0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1. \tag{20}$$

The choice of the better technology is based on adaptive learning, and farmers switch to a better technology if the profits from adopting that technology in the previous period are positive and given as $\theta + \varepsilon$, where ε is a randomly distributed variable. The probabilities of forward and backward steps are given by

$$\begin{aligned} p\left(x\left(\frac{1}{4}\right) \rightarrow x\left(\frac{1}{2}\right)\right) &= p(\varepsilon > -\theta), \\ p\left(x\left(\frac{1}{2}\right) \rightarrow x\left(\frac{1}{4}\right)\right) &= p(\varepsilon < -\theta). \end{aligned} \tag{21}$$

By means of the above assumption, I derive the steady-state level of adoption of technology for the Mississippi region as given below:

(22)

$x(0)$	$x(1/4)$	$x(1/2)$	$x(3/4)$	$x(1)$
0.0005	0.0033	0.0212	0.1335	0.8413

Note that in the long term, the entire region of Mississippi would end up adopting the technology 84% of the time. This is slightly lower than the probability of adoption as derived in Table 1. When adoption inertia is low, I can assume that a larger fraction of the population makes the decision to adopt the spraying technology in any given time period. Let the new state space be $x_t = 0$, ½, and 1, following which the long-term steady-state is derived as

(23)

$x(0)$	$x(1/2)$	$x(1)$
.021	.134	.845

Table 4. Adoption Data for Heartland

Heartland	Treat	No Treat	Difference
Not infested (profits—\$/acre)	152.97	177.97	−25
Infested (profits—\$/acre)	145.02	0	145.02
Range of difference (\$/acre)			170.02
F(d)~U	0.00588		
P(adoption)	0.8529		
P(disadoption)	0.1470		

Table 5. Steady-State Distribution in the Nine Possible States

	$x0y0$	$x0y0.5$	$x0y$	$x0.5y0$	$x0.5y0.5$	$x0.5y$	$xy0$	$xy0.5$	xy
Row 1	0.0005	0.0033	0.0206	0.0030	0.0192	0.1209	0.0179	0.1116	0.7026
Row 2	0.0005	0.0031	0.0213	0.0026	0.0172	0.1182	0.0171	0.1046	0.7151
Row 3	0.0007	0.0086	0.0635	0.0028	0.0257	0.1897	0.0168	0.0906	0.6012
Row 4	0.0012	0.0315	0.2335	0.0045	0.0340	0.2764	0.0148	0.0596	0.3444

Notice a slight increase in the fraction of time when the entire population ends up adopting the new technology. In fact, as the inertia falls, the long-term steady-state fraction of time would end up equaling the probability of adoption.

Now, consider when the adoption of technology in one region influences the adoption in the other region. Farmers in the Heartland region (see Table 4) wait and watch the advent of soybean rust in the Mississippi region each year and, based on the level of infestation and the measures taken by Mississippi farmers, form opinions on the risk of spread into the Heartland region. Following the model in section 2, I assume that the farmers in the Heartland have a complacency effect that kicks in whenever the technology adoption level in the Mississippi region reaches a certain threshold. Using the profits net of variable costs, as derived in the tables, I design the long-run steady-state distribution of technology adoption within the two regions. The state space is defined as

$$x0y0 \quad x0y0.5 \quad x0y \quad x0.5y0 \quad x0.5y0.5 \quad x0.5y \quad xy0 \quad xy0.5 \quad xy \tag{24}$$

where $x0y0$ stands for the fraction of time when both regions show zero adoption.

For Mississippi, $\sigma = 91.25$, $\theta = 66.26$, and $m = 0$, and for the Heartland, $\sigma = 85.012$, $\theta = 60.012$, $m = 0$, and $q = 0$. The steady-state distribution is now derived as row 1 of Table 5. Notice that when the complacency effect is assumed to be zero, both the regions end up adopting the spraying technology 70% of the time. Now, increase the popularity weighting factor m to 2. For Mississippi, $\sigma = 91.25$, $\theta = 66.26$, and $m = 2$, and for the Heartland, $\sigma = 85.012$, $\theta = 60.012$, $m = 2$, and $q = 1$; the steady-state distribution of times spent in each of these states is now derived as row 2 of Table 5. An increase in the popularity weighting factor with a small increase in the complacency effect leads to an increase in the fraction of time spent in the state when both regions are fully adopted. When the complacency effect for the Heartland region is increased to $q = 20$, the steady-state distribution of times spent in each of the states is now given as row 3 of Table 5. When the complacency effect for the Heartland region is increased to $q = 60$, the steady-state distribution of times spent in each of the states is now given as row 4 of Table 5.

Notice now that an increase in the complacency effect leads to a dramatic fall in the fraction of time spent in the state when both regions are fully adopted. Also note that region x shows a strong negative correlation with region y in terms of the fraction of population that has adopted the technology. For instance, when y is fully adopted, the probabilities of region x being fully disadopted or 50% adopted are 0.23 and 0.27, respectively.

The above analysis assumes that level of adoption in the Mississippi region has no impact on the level of pest infestation. Similarly, the long-term pest infestation may be determined by the level of adoption in both the regions, and it is likely that, over time, the distribution of profits will shift toward the positive side with continued adoption and toward the negative side with low levels of adoption. But, at this stage, there is not much empirical evidence to incorporate the endogeneity in the probability of adoption brought in by its impact on the pest population.

Although complacency is one aspect of technology adoption, compulsion may have an equally significant role to play. If farmers insure themselves against pest damages, good management practices require that they spray their crops with fungicides whenever it is required. Failure to follow this protocol might lead to a loss in compensation payment from the insuring agency. Also, if spraying by the neighbor increases the risk of infestation on one's own fields, the farmer might be forced to adopt spraying.

Conclusion

Technology adoption against invasive species is guided by several motives, as has been demonstrated in this article. Psychological factors, such as complacency and learning from neighbors, could play a crucial role in this process. There could also be a role for public intervention. The existing literature on technology adoption distinguishes between technology that is embodied in capital goods and is much easier to adopt and technology that is disembodied and not that easy to adopt (Sunding and Zilberman). The technological advances against invasive species fall under the latter category and may therefore require government participation (Sunding and Zilberman).

In this article, I demonstrated that technology adoption may not be fully realized because of the complacency of nonadopters. Other factors that feed into these effects are dependent on the unique characteristics of the invading pests. The application to soybean rust portrays a good possibility of these effects showing up and influencing the technology adoption processes. Very little is observable in terms of actual technology adoption at this stage because of the nascent nature of pest infestation, but chances are good that the compulsion effect will dominate the complacency effect. This is because of the heavy damages caused by soybean rust in Brazil and the observed behavior of soybean growers in the United States so far who have demonstrated a very keen interest in keeping track of the day-to-day migration of rust spores within the United States. Much work remains to be done in terms of eliciting farmers' responses to soybean rust outbreaks in their neighborhood in order to be able to understand adoption behavior. With a large number of pests invading the same crops in the future, due to the increasing rates of alien infestation in the United States, it is likely that the rate and nature of technology adoption by farmers will become a more complex process.

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Appendix

Matrix for Steady State Calculation:

$$\left\{\left\{\left(1-\frac{-m+\theta+\sigma}{2\sigma}\right)\left(1-\frac{q+\theta+\sigma}{2\sigma}\right),\frac{(-m+\theta+\sigma)\left(1-\frac{-m+q+\theta+\sigma}{2\sigma}\right)}{2\sigma},\right.\right.$$

$$\left.0,\frac{(-m+q+\theta+\sigma)\left(1-\frac{-m+\theta+\sigma}{2\sigma}\right)}{2\sigma},\frac{(-m+\theta+\sigma)(-m+q+\theta+\sigma)}{4\sigma^2},0,0,0,0\right\},$$

$$\left\{\left(1-\frac{\theta+\sigma}{2\sigma}\right)\left(1-\frac{-m+\theta+\sigma}{2\sigma}\right),0,\frac{(\theta+\sigma)\left(1-\frac{-m+\theta+\sigma}{2\sigma}\right)}{2\sigma},\frac{(-m+\theta+\sigma)\left(1-\frac{\pm\theta+\sigma}{2\sigma}\right)}{2\sigma},\right.$$

$$\left.0,\frac{(\theta+\sigma)(-m+\theta+\sigma)}{4\sigma^2},0,0,0\right\},$$

$$\left\{0,\left(1-\frac{m+\theta+\sigma}{2\sigma}\right)\left(1-\frac{-m-q+\theta+\sigma}{2\sigma}\right),\frac{(m+\theta+\sigma)\left(1-\frac{-m-q+\theta+\sigma}{2\sigma}\right)}{2\sigma},\right.$$

$$\left.0,\frac{(-m-q+\theta+\sigma)\left(1-\frac{m+\theta+\sigma}{2\sigma}\right)}{2\sigma},\frac{(m+\theta+\sigma)(-m-q+\theta+\sigma)}{4\sigma^2},0,0,0\right\},$$

$$\left\{\left(1-\frac{-m+\theta+\sigma}{2\sigma}\right)\left(1-\frac{q+\theta+\sigma}{2\sigma}\right),\frac{(-m+\theta+\sigma)\left(1-\frac{q+\theta+\sigma}{2\sigma}\right)}{2\sigma},\right.$$

$$\left.0,0,0,0,\frac{(q+\theta+\sigma)\left(1-\frac{-m+\theta+\sigma}{2\sigma}\right)}{2\sigma},\frac{(-m+\theta+\sigma)(q+\theta+\sigma)}{4\sigma^2},0\right\},$$

$$\left\{\left(1-\frac{\theta+\sigma}{2\sigma}\right)^2,0,\frac{(\theta+\sigma)(1-\frac{\theta+\sigma}{2\sigma})}{2\sigma},0,0,0,\frac{(\theta+\sigma)(1-\frac{\theta+\sigma}{2\sigma})}{2\sigma},0,\frac{(\theta+\sigma)^2}{4\sigma^2}\right\},$$

$$\left\{0,\left(1-\frac{m+\theta+\sigma}{2\sigma}\right)\left(1-\frac{-q+\theta+\sigma}{2\sigma}\right),\frac{(m+\theta+\sigma)\left(1-\frac{-q+\theta+\sigma}{2\sigma}\right)}{2\sigma},\right.$$
$$\left.0,0,0,0,\frac{(-q+\theta+\sigma)(1-\frac{m+\theta+\sigma}{2\sigma})}{2\sigma},(m+\theta+\sigma)\left(1-\frac{-q+\theta+\sigma}{4\sigma^2}\right)\right\},$$

$$\left\{0,0,0,\left(1-\frac{-m+\theta+\sigma}{2\sigma}\right)\left(1-\frac{m+q+\theta+\sigma}{2\sigma}\right),\frac{(-m+\theta+\sigma)\left(1-\frac{m+q+\theta+\sigma}{2\sigma}\right)}{2\sigma},\right.$$
$$\left.0,\frac{(m+q+\theta+\sigma)(1-\frac{-m+\theta+\sigma}{2\sigma})}{2\sigma},\frac{(-m+\theta+\sigma)(m+q+\theta+\sigma)}{4\sigma^2},0\right\},$$

$$\left\{0,0,0,\left(1-\frac{\theta+\sigma}{2\sigma}\right)\left(1-\frac{m+\theta+\sigma}{2\sigma}\right),0,\frac{(\theta+\sigma)(1-\frac{m+\theta+\sigma}{2\sigma})}{2\sigma},\frac{(m+\theta+\sigma)(1-\frac{\theta+\sigma}{2\sigma})}{2\sigma},\right.$$
$$\left.0,\frac{(\theta+\sigma)(m+\theta+\sigma)}{4\sigma^2}\right\},$$

$$\left\{0,0,0,0,\left(1-\frac{m+\theta+\sigma}{2\sigma}\right)\left(1-\frac{m-q+\theta+\sigma}{2\sigma}\right),\frac{(m+\theta+\sigma)\left(1-\frac{m-q+\theta+\sigma}{2\sigma}\right)}{2\sigma},\right.$$
$$\left.0,\frac{(m-q+\theta+\sigma)(1-\frac{m+\theta+\sigma}{2\sigma})}{2\sigma},\frac{(m+\theta+\sigma)(m-q+\theta+\sigma)}{4\sigma^2}\right\}\Bigg\}.$$

Note: This is a 9×9 matrix where each row is represented by a brace containing 9 elements. The nine states of the system are given as: $\{x0y0,\ x0y.5,\ x0y,\ x.5y0,\ x.5y.5,\ x.5y,\ xy0,\ xy.5,\ xy\}$