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Technology Adoption against Invasive Species

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Abstract

This paper explores the issue of 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 dis-adopted based upon current and expected agricultural profits which are influenced by the state of pest infestation. The impact of adaptive learning on adoption of technology is analyzed in the setting of complacency set in from a reduction in risks or compulsion to adopt technology from reduced profitability in event of non-adoption. Possibility of eradication of the disease based upon long term adoption of technology is also explored. The theoretical analysis confirms the intuition that psychological factors such as complacency may have a significant impact on technology adoption and hence disease eradication. Further, learning from neighbors may not necessarily lead to higher technology adoption. In fact, overall adoption may go down based upon the level of complacency prevalent in masses. An empirical application is performed for the case of soybean rust. Findings indicate that the role of psychological perceptions may play a role in disease spread in the short run. The long term spread and establishment of the disease would be determined by nature and speed of the learning process for the farmer over the pest's optimal management strategy.

Keywords: soybean rust, technology adoption, invasive species, complacency, and compulsion

1. Introduction

Several features differentiate technology adoption specifically targeted against invasive species from the conventional technology adoption geared towards increasing productivity in agriculture. For one, the adoption and dis-adoption of technology may be correlated with pest population. A reduction or elimination of pest population may lead to dis-adoption of that technology. Second, technology itself may continue to change faster than the rate of adoption due to the need to incorporate resistance/control of multiple pests, consumer reaction, productivity effects, etc¹. Finally, technology adoption in conventional agriculture is geared towards attaining higher profitability, whereas the immediate aim of technology adoption against invasives is mostly preventative in nature and therefore is subject to fluctuations borne out by adopter's psychological responses such as complacencies or compulsions.

Technology adoption is significantly influenced by learning by doing or observing, as has been argued in the literature. However, in case of adoption of a new technology in order to ward off a threat from invasion species, complacency may play a crucial role in determining its extent of adoption and consequently decide the eventual eradication or establishment of the pest. Geoffard (1997) points out that vaccination demand for diseases such as tuberculosis, influenza, etc. falls as the prevalence of the disease in the population falls. This phenomenon, characterized as the prevalence effect, may also be found in the case of invasive species that threaten agriculture. Farmers, whose crops have not yet been infected with invasive species, might wait until the pest

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.

arrives as close to the neighbor's farm. This complacency may also be aggravated by the presence of government indemnity programs and insurance schemes that aim to compensate the farmer in the wake of damages from infestation, without imposing good farming practices. Empirical work on measuring or explaining the extent of complacency effects is still missing, but its existence has also been discerned in several other fields. Sterman and 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 in relating flows in and out of stock to the trajectory of stock'. Consequently, the stock of carbon is understood to be falling with reduction of emissions, even as the net inflow into stock may be positive. This behavior is also explained by pattern matching heuristics (Sterman and Booth Sweeny 2002). Complacency against infectious diseases may have similar origins; people relating 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.

Opposite to complacency effect, certain factors such as the influence of 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 such kinds of technology adoptions. Whether or not forces influencing technology adoption are of 'complacency type' or 'compelling type' would depend upon pest characteristics, its modes of transport, and several other regional, social and behavioral factors.

In this paper we look at the issue of technology adoption in agriculture that is directed towards combating invasive species. We build on the previous literature on technology adoption that highlights the role of adaptive learning in the process of technology adoption (for instance Ellison and Feudenberg 1993 & 1995). 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. While mass media creates awareness, interpersonal communication is more crucial in transferring technical knowledge to farmers (Longo 1990).

The analysis in this paper involves looking at the long term distribution of technology choices when technology can be adopted and dis-adopted based upon current and expected profits in agriculture. The impact of adaptive learning on adoption of technology is analyzed in the setting of complacency effect set in from a reduction in risks or compulsion to adopt technology in wake of reduced expected profitability from not doing so. Possibility of eradication of the disease based upon long term adoption of technology is also explored. The theoretical analysis confirms the intuition that psychological factors such as complacency may have a significant impact on technology adoption and hence disease eradication. Further, learning from neighbors may not necessarily lead to higher technology adoption. In fact, overall adoption may go down based upon the level of complacency prevalent in masses.

An empirical analysis is also performed for the recent case of soybean rust advent into the United States². Even though the pest has arrived into the US, the infestation rates

² In terms of soybean yield differences amongst farmers, technology adoption has been believed to be a deciding factor. Those farmers who are able to exploit better technology can produce soybean at a cost of

so far have been fairly low. However, significant threat exists for future cases of severe infestation if adequate preventative measures are not taken into account. This threat is further compounded by extreme weather events such as hurricanes that are capable of transforming soybean spores to far off places. Due to the spatial and temporal differences in soybean infestation within the various soybean growing regions of the US, there is a 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 would be determined by nature and speed of the learning process for the farmer over the pest's optimal management strategy.

2. 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. The difference in the payoffs between these two technologies is given by: $U^g - U^f \geq \theta + \varepsilon$, where θ is the deterministic component of payoff differential and ε is the stochastic component with a uniform distribution. Following the mathematical approach in Ellison and Feudenberg (1993), we assume that the farmers' decision to adopt technology g is based upon 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

\$2bu/acre as compared to \$10bu/acre for those who don't (Wherspann 2003). In general, the rate of technology adoption has been found to be quite significant in agriculture in certain areas. Fernandez et al. (2003) find that the adoption of herbicide tolerant soybeans rose from 17 percent in 1997 to about 81 percent in 2003 for the United States.

farmers (x), who have already adopted the better technology. The farmers' decision problem is then to: Choose g if $U^g - U^f \geq m(1 - 2x)$. 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 .5 or more for x in the above equation, which turns the right hand side negative.

We incorporate 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 in cases where an increase in the level of adoption has a negative influence on rate of infestation, thus reducing its risk of further spread. When this happens, a marginal increase in 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 threats have reduced. This possibility would lead to switching when: $U^g - U^f \geq m(1 - 2x) - q(1 - kx)$, where q is the parameter that influences the level of complacency and k determines the level of adopted population beyond which complacency sets in. Following the analysis in Ellison and Feudenberg (1993) we derive the dynamics of agricultural technology adoption and conditions for full technology adoption. Ellison and Feudenberg (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 invasive species, this can be thought of as a spatial parameter which may relate to the proximity of the population that is up for choice, to the population that has already adopted the better technology. The increase in population that adopts the technology is then given by the rule:

$$(1) \quad x(t+1) = x(t) + \alpha(1 - x(t)) - > P[1 - H(m(1 - 2x) - q(1 - kx) - \theta)]$$

where H is the cumulative distribution function of the random term ε . 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 profits θ . Similarly, the conditions for a downward movement in x are given by:

$$(2) \quad x(t+1) = (1-\alpha)x(t) - > P[H(m(1-2x) - q(1-kx) - \theta)]$$

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

$$(3) \quad \theta + \varepsilon \geq (m(1-2x) - q(1-kx))$$

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

$$(4) \quad x(t) \geq x^g \equiv \theta - \sigma \geq m(1-2x) - q(1-kx)$$

which gives:

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

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

$$(6) \quad x(t) \leq x^f \equiv \theta + \sigma \leq m(1-2x) - q(1-kx), \text{ which gives:}$$

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

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

$$(8) \quad P(\theta + \varepsilon \geq m - q), \text{ or,}$$

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

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

$$(10) \quad P(\theta + \varepsilon \leq -m - q + qk), \text{ or,}$$

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

From above Ellison and Feudenberg derive the conditions for convergence of the technology as:

$$(12) \quad x^g < 1, x^f < 0 \Rightarrow x(t) \rightarrow 1$$

$$(13) \quad x^g > 1, x^f > 0 \Rightarrow x(t) \rightarrow 0$$

$$(14) \quad x^g > 1, x^f < 0 \Rightarrow \text{no convergence}$$

$$(15) \quad x^g < 1, x^f > 0, \text{ if } x_0 > x^g \Rightarrow x(t) = 1, \text{ however if } x_0 < x^f \Rightarrow x(t) = 0$$

Condition (12) implies that the better technology will eventually get adopted if

$$x^g < 1, x^f < 0. \text{ Also note that when } m - q = \sigma, \text{ and } q < 2: x^g < \frac{2(m - q) - \theta}{2m - qk} < 1, \text{ and}$$

$$x^f = \frac{(m - q - \theta - \sigma)}{2m - qk} < 0. \text{ Therefore, when the popularity weighting impact net of any}$$

complacency impact equals the maximum range of the random error, the entire population converges towards the better technology. Ellison and Feudenberg characterize this as the optimal weighting scheme as convergence happens with probability one. 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 upon the starting point.

Now, let's derive the conditions for convergence when complacency effect dominates popularity weighting. Specifically, the condition for a forward step with certainty is: $\theta - \sigma \geq m(1 - 2x) - q(1 - kx)$. Since, in this case $q > m$, the lower the value

of x , the higher would be the probability of a forward jump. Therefore, a forward jump happens with certainty when: $x \leq x^g \equiv (\frac{k-m+\theta-\sigma}{-2m+qk})$. Similarly, a backward jump happens with certainty when: $x \geq x^f \equiv (\frac{k-m+\theta+\sigma}{-2m+qk})$.

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 towards the conventional technology with positive probability if $x^g < 0$.

While the above setting assumes a linear equation between popularity and complacency effect, thus allowing the stronger effect to dominate, complacency effect may also be non-linear in 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 significant threat from the pest. Such, a relationship, however, is entirely governed by how pest infestation is influenced by technology adoption.

2.1 Some Extensions

Now, let us 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 we discuss that

in the ensuing sections. Finally, non-linearity in the profit differential is also taken up in this section.

2.1.1 Difference in Payoffs is increasing in Adoption

The payoff differential may be increasing with adoption of the new technology if the impact of the pest is increasing in proportion to the population using 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 using the older technology. Such a payoff differential can be thought of as being dependent upon the proportion using the new technology as θx .

2.1.2 Difference in Payoffs is falling in Adoption

Difference in payoffs could also be falling in profits due to several reasons. First, if the impact of the invasive plant falls with the level of adoption, making it impossible for the pest to establish once the host population (given by the percentage of population using 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 (using old technology) increase due to consumer skepticism and reluctance to try new varieties. Profits may fall also from an increased supply of the

agricultural commodity in the market caused by the new technology. In certain cases the new technology may also end up adversely affecting other pests of the commodity thus increasing productivity (Livingston et al. 2004). If the demand for the agricultural commodity is highly inelastic, this might cause a reduction in overall profits for every one. Finally, heterogeneity in population given by differences in production costs would lead to farmers with higher costs postponing their adoption until later on. When this happens, there may be threshold level of population for technology adoption beyond which it is optimal for the farmers still using the conventional technology not to adopt.

Consider the possibility that the payoff differential is falling as given by: $\theta(1-x)$. A farmer would choose the better technology if: $\theta(1-x) + \varepsilon \geq m(1-2x)$. Now, the value of x beyond which a forward step is possible with certainty is given by:

$x \geq x^{g*} \equiv \frac{m-\theta+\sigma}{2m-\theta}$. The value of x below which a backward step is possible with

certainty is given by: $x \leq x^{f*} \equiv \frac{-\sigma+m-\theta}{2m-\theta}$. When the payoff differential remains

constant equal to θ , the same cut-offs are given as:

$x \geq x^g \equiv \frac{m-\theta+\sigma}{2m}$ $x \leq x^f \equiv \frac{-\sigma+m-\theta}{2m}$. Consequently, a falling differential shifts the

cutoffs towards the right as shown below. Intuitively, it becomes much easier for the system to move towards the conventional technology and away from the better one.

$$\xrightarrow{\quad x^f \quad x^{f'} \quad \quad x^g \quad x^{g'} \quad}$$

2.1.3 Difference in payoffs is non-linear in adoption

Non-linearity in adoption may arise from several reasons. For one, if the new technology is a biologically altered plant variety that may be resistant to pests or herbicides, its profitability may depend upon several key factors including public preferences for the new food, overall market size, etc. 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 the new technologies may turn from positive to negative as the adoption level for the new technology increases. Consider the case for 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 lower population producing it, the prices may increase, thus making lower technology more profitable. This non-linearity can be incorporated by assuming that the payoff function is non-linear and given by: $\theta \cos [3x]$. Figure 1 below shows the profit differential as the level of adoption increase from 0 to 1.

INSERT FIGURE 1 HERE

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

and 3. As is 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 non-linearity in the profit function and the ensuing dis-incentive to adopt marginally at high stages of adoption and dis-adopt marginally at low stages of overall adoption. Now, let us consider the long term distribution of the system. For $m=2; \theta=2; \sigma=5$; the steady state distribution of the system between discrete states of adoption defined as: $x(t) = 0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1$ is given by: 0.18, 0.19, 0.21, 0.21, 0.20. As is evident from above, all states are equally attractive in the long run.

3. Technology Adoption and Disease Eradication

Heterogeneity in the population can be present due to several reasons such as differences in production and treatment costs, differences in the age, education and risk perception of the population etc. However, spatial heterogeneity may be another key factor that may have a significant impact on the level of adoption. So far in the above sections we have concentrated upon the level of technology adoption without paying any attention to how it may have an impact on disease spread and eradication. It is obvious that less than full adoption may have a bearing on the long term impact of the disease and we saw several cases above where the better technology could not be adopted with probability one. In this section we 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 impacted first. Region x demonstrates complacency in adoption which is given by: $\theta + \varepsilon \geq m(1 - 2x) - q(1 - 2y)$. This complacency in

adoption is not only based upon adoption within region x but 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: $\theta + \varepsilon \geq (m(1 - 2y))$. Probability of a forward step for region x is given by:

$$(16) \quad P[\theta + \varepsilon \geq (m(1 - 2x) - q(1 - 2y))] = \frac{\sigma + \theta + q(1 - 2y) - m(1 - 2x)}{2\sigma}$$

Probability of a forward step for region y is given by:

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

Now, in order to look at the steady state distribution of the system, we divide the state space into nine parts as follows:

$$(18) \quad \{x_0y_0, x_0y_{.5}, x_0y, x_{.5}y_0, x_{.5}y_{.5}, x_{.5}y, xy_0, xy_{.5}, xy\}$$

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

$$(19) \quad \begin{array}{ccccccccc} x_0y_0 & x_0y_{.5} & x_0y & x_{.5}y_0 & x_{.5}y_{.5} & x_{.5}y & xy_0 & xy_{.5} & xy \\ .0059 & .0166 & .1426 & .0067 & .0178 & .1557 & .0570 & .0818 & .5155 \end{array}$$

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: ($\sigma=5$; $\theta=2$; $m=2$; $q=4$); the steady state distribution is now given as:

$$(20) \quad \begin{array}{ccccccccc} x0y0 & x0y.5 & x0y & x.5y0 & x.5y.5 & x.5y & xy0 & xy.5 & xy \\ .0097 & .0592 & .5546 & .0067 & .0083 & .1315 & .0531 & .0486 & .1277 \end{array}$$

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. We define parameters $t1...t9$ that replace θ depending upon the level of adoption in the two regions combined. The new set of parameters is:

$$\text{sigma}=5;\text{theta}=2;m=2;q=1;t1=0;t2=.5;t3=1;t4=.5;t5=1;t6=1.5;t7=1;t8=1.5;t9=2;$$

The steady state distribution (say for the base case) is now defined as:

$$(21) \quad \begin{array}{ccccccccc} x0y0 & x0y.5 & x0y & x.5y0 & x.5y.5 & x.5y & xy0 & xy.5 & xy \\ .0384 & .0409 & .1581 & .0270 & .0259 & .1273 & .0915 & .0822 & .4083 \end{array}$$

Obviously, an increase in profitability from adoption provides added incentive to adopt as is evident from the new steady state distribution. When profits are falling in adoption, which could happen due to an increase in productivity from a better technology adoption, there may exist an incentive not to adopt. For the parameters: $\text{Sigma}=5;\text{theta}=2;m=2;q=1;t1=2;t2=1.5;t3=1;t4=1.5;t5=1;t6=.5;t7=1;t8=.5;t9=0$; the steady state distribution is given as;

$$(22) \quad \begin{array}{ccccccccc} x0y0 & x0y.5 & x0y & x.5y0 & x.5y.5 & x.5y & xy0 & xy.5 & xy \\ .0316 & .0589 & .2063 & .0414 & .0517 & .1388 & .1523 & .1201 & .1984 \end{array}$$

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:

$\sigma=5; \theta=2; m=2; q=1; t_1=0; t_2=.5; t_3=1; t_4=.5; t_5=1; t_6=1.5; t_7=1; t_8=1.5; t_9=2;$

We 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 $t_1 \dots t_9$ 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 dis-adopted doubles from the base case.

An Application to Soybean Rust

Soybean rust, a disease of the soybean and several other plant species has been threatening the US soybean crop since it arrived in 2004. Though the threat was reduced in 2005 due to limited infestations during the crop season, potential for the pest becoming endemic are serious and call for long term planning to manage this pest. Soybean rust is chiefly windborne and is capable of trans-continental migrations helped by favorable events such as hurricanes. In fact, hurricane Ivan of 2004 is suspected as medium for bringing soybean rust from South America³. Soybean rust could cause significant damages to the US soybean crops, and available estimates in the literature project losses of up to US \$7.2 billion/year from the disease (APHIS USDA 2004).

³ “The most likely scenario as to how soybean rust arrived in the continental United States is via Hurricane Ivan. Ivan formed in the Atlantic in early September, brushed the South American coast, and proceeded to strike the southeastern United States, carrying rust spores from Colombia and Venezuela”. (Hart 2005).

Management of soybean rust would require significant private participation involving soybean growing farmers in the States in order to monitor and control its yearly migration across regions. Due to its ability to survive in cool and wet climates, it is possible for the rust to over-winter 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 it through public policies. Crop rotations, such as switching between soybean 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 sub-optimum crop rotations and the risk perception of the farmers. Similarly, decision over how much or whether or not to spray are influenced by risk perceptions and could vary from location to location based upon farmer and regional heterogeneity. Adaptive management of crops faced with threat of invasion can be expedited by public policies that reward socially optimum practices. For this to be possible, an understanding of farmer's learning capabilities under various infestation scenarios is crucial as it would help policy makers be a leg up in terms of public inducement programs.

Herein, we select two regions, the Mississippi delta and the US Heartland for analysis. The total average profits for the years 2003 and 2004 in the two regions, net of operating costs, are presented in the tables below. 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 positive whenever the profits are in the non-negative range. For simplicity, we assume that currently there are no complacency effects. Next, we 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:

$$(23) \quad x(t) = 0, \frac{1}{4}, \frac{1}{2}, \frac{3}{4}, 1$$

The choice of the better technology is based upon 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:

$$(24) \quad \begin{aligned} p(x(\frac{1}{4}) \rightarrow x(\frac{1}{2})) &= p(\varepsilon > -\theta) \\ p(x(\frac{1}{2}) \rightarrow x(\frac{1}{4})) &= p(\varepsilon < -\theta) \end{aligned}$$

Using the above assumption, we derive the steady state level of adoption of technology for the Mississippi region as given below:

$$(25) \quad \begin{array}{ccccc} 0 & 1/4 & 1/2 & 3/4 & 1 \\ .0005 & .0033 & .0212 & .1335 & .8413 \end{array}$$

Note that in the long term, the entire region of Mississippi would end up adopting the technology 84 percent of the time. This is slightly lower than the probability of adoption as derived in table 1. When adoption inertia is low, we 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 $x(t) = 0, \frac{1}{2}, 1$, following which the long term steady

state is derived as:

$$(26) \quad \begin{array}{ccc} 0 & 1/2 & 1 \\ .021 & .134 & .845 \end{array}$$

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, let us consider the case when adoption of technology in one region influences adoption in the other region. Farmers in the Heartland region (see Table 2) wait and watch the advent of soybean rust in the Mississippi region each year and based upon the level of infestation and the measures taken by Mississippi farmers, form opinion over the risk of spread into the Heartland region. Following the model in section 3, we assume that the farmers in the Heartland region have a complacency effect which 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; we design the long run steady state distribution of technology adoption within the two regions. The state space is defined as:

$$(27) \quad \begin{array}{cccccccccc} x_0 & y_0 & x_0 & y_{.5} & x_0 & y & x_{.5} & y_0 & x_{.5} & y_{.5} & x_{.5} & y & x_y & y_0 & x_y & .5 & x_y \end{array}$$

where $x_0 y_0$ stands for the fraction of time when both regions show zero adoption.

For Mississippi, $\sigma = 91.25$ $\theta = 66.26$, $m = 0$, and for the Heartland $\sigma = 85.012$, $\theta = 60.012$, $m = 0$, $q = 0$. The steady state distribution is now derived as:

$$(28) \quad \begin{array}{ccccccccc} x_0y_0 & x_0y.5 & x_0y & x.5y_0 & x.5y.5 & x.5y & xy_0 & xy.5 & xy \\ .0005 & .0033 & .0206 & .0030 & .0192 & .1209 & .0179 & .1116 & .7026 \end{array}$$

Notice that when complacency effect is assumed to be zero, both the regions end up adopting the spraying technology seventy percent of the time. Now let us increase the popularity weighting factor m to 2. For Mississippi, $\sigma = 91.25$ $\theta = 66.26$, $m = 2$ and for the Heartland $\sigma = 85.012$ $\theta = 60.012$ $m = 2$ $q = 1$, the steady state distribution of times spent in each of these states is now derived as:

$$(29) \quad \begin{array}{ccccccccc} x_0y_0 & x_0y.5 & x_0y & x.5y_0 & x.5y.5 & x.5y & xy_0 & xy.5 & xy \\ .0005 & .0031 & .0213 & .0026 & .0172 & .1182 & .0171 & .1046 & .7151 \end{array}$$

An increase in the popularity weighting factor 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:

$$(30) \quad \begin{array}{ccccccccc} x_0y_0 & x_0y.5 & x_0y & x.5y_0 & x.5y.5 & x.5y & xy_0 & xy.5 & xy \\ .0007 & .0086 & .0635 & .0028 & .0257 & .1897 & .0168 & .0906 & .6012 \end{array}$$

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:

$$(31) \quad \begin{array}{ccccccccc} x_0y_0 & x_0y.5 & x_0y & x.5y_0 & x.5y.5 & x.5y & xy_0 & xy.5 & xy \\ .0012 & .0315 & .2335 & .0045 & .0340 & .2764 & .0148 & .0596 & .3444 \end{array}$$

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 strong negative correlation with region y in terms of fraction of

population that has adopted the technology. For instance, when y is fully adopted, the probabilities of region x being fully dis-adopted or fifty percent adopted are .23 and .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 would shift towards the positive side with continued adoption and towards the negative side with low levels of adoption. But, at this stage there is not much empirical evidence to incorporate the endogeneity in probability of adoption brought in by its impact on pest population.

While 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 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 paper. Psychological factors such as complacency and learning from neighbors could play a crucial role in this process. The existing literature on technology adoption does not provide much guidance over the long term state of technology adoption against invasive species. Yet, long term adoption rates are very

significant to understand from policy perspective as they determine whether or not a pest will become endemic.

In this paper, we demonstrated that technology adoption may not be fully realized due to several factors. Chief amongst them are compulsion and complacency. Other factors that feed into these effects are dependent upon the unique characteristics of the invading pests. The application to soybean rust portrays a good possibility of these effects showing in and influencing the technology adoption processes. Very little is observable in terms of actual technology adoption at this stage due to the nascent nature of pest infestation, but chances are good that compulsion effect might dominate the complacency effect. This is due to the heavy damages caused by soybean rust in Brazil and the observed behavior of soybean growers in the US so far who have demonstrated a very keen interest in keeping track of the day to day migration of rust spores over the United States. Much work remains to be done in terms of eliciting farmer's response to soybean rust outbreaks in his neighborhood in order to be able to understand adoption behavior. With a large number of pest invading same crops in future, due to increasing rates of alien infestation in the US, it is likely that the rate and nature of technology adoption by farmers would become a more complex process not easily discernable. It is very likely that farmer types characterized by size of farm, education, income, etc. would have an increasingly key role to play in determining who adopts and who does not.

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Appendix

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

Note: This is a 9X9 matrix where each row is represented by a parenthesis containing 9 elements. The nine states of the system are given as:

$\{x_0y_0, x_0y_5, x_0y, x_5y_0, x_5y_5, x_5y, xy_0, xy_5, xy\}$

Mississippi	Treat	No-Treat	Difference
Not-Infested	165.93	190.93	-25
Infested	157.51	0	157.51
Range of Difference			182.51
F(d)~U	.005479		
P(adoption)	.863028		
P(disadoption)	.136972		

Table 1: Adoption Data for Mississippi

Heartland	Treat	No-Treat	Difference
Not-Infested	152.97	177.97	-25
Infested	145.02	0	145.02
Range of Difference			170.02
F(d)~U	.00588		
P(adoption)	.8529		
P(disadoption)	.1470		

Table 2: Adoption Data for Heartland

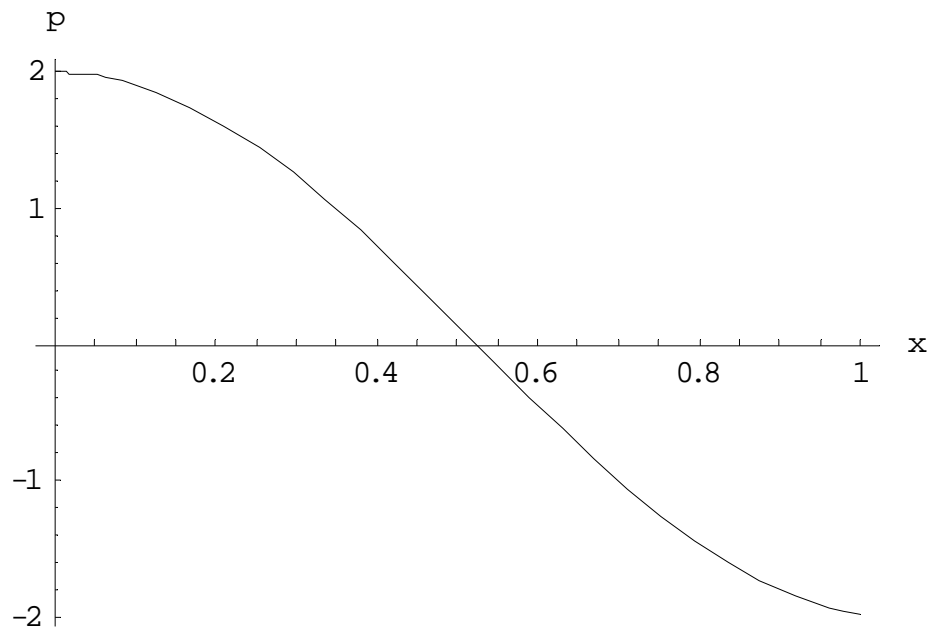


Figure 1: Profit Differential with a Change in the Level of Adoption

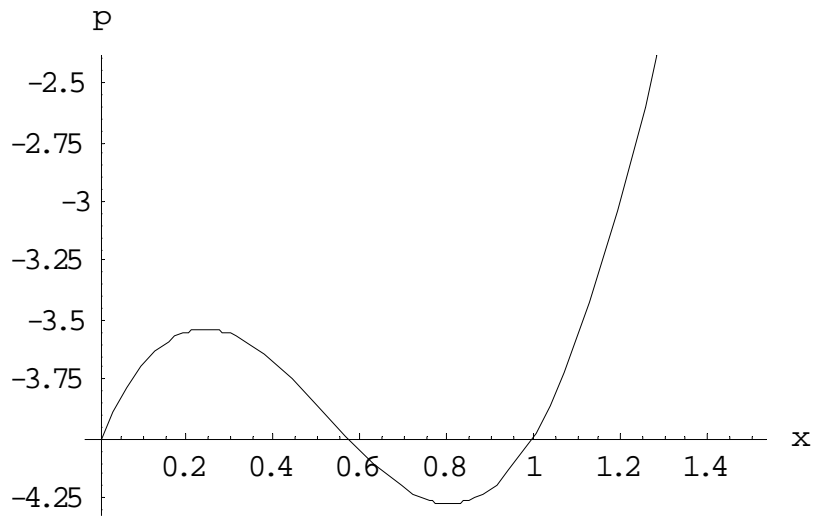


Figure 2: Certainty of a Forward Movement

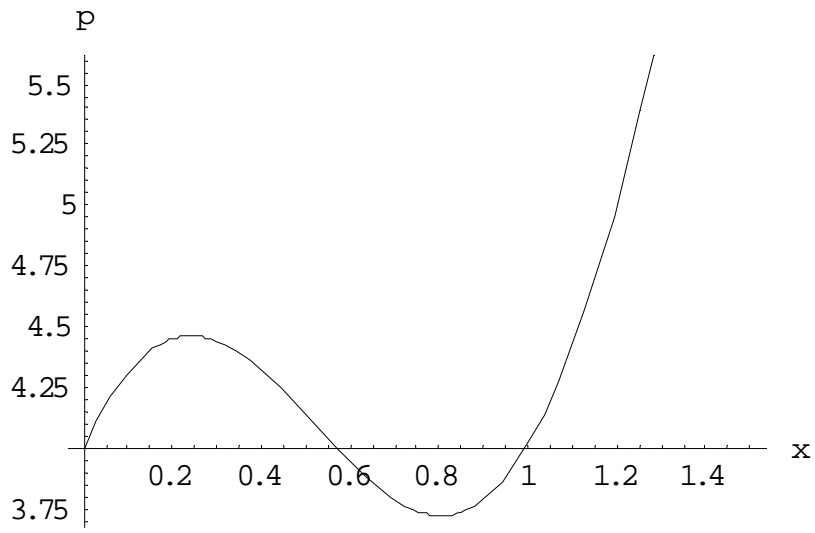


Figure 3: Certainty of a Backward Movement