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Impacts of Microbial Inoculants as Integrated Pest Management Tools in Apple Production

Holcer Chavez, Denis Nadolnyak, and Joseph W. Kloepper

This article analyzes the impacts of microbial inoculant (MI) technology, which is a part of integrated pest management, on the U.S. apple production using farm-level data. To test the likely production impacts suggested by agronomic literature, we estimate a pesticide use function and stochastic production functions with damage control input specification. The results show that although adoption of the MI technology does not reduce the use of pesticides, the technology has a significant positive impact on yields and is associated with higher technical production efficiency rates.

Key Words: apple production, microbial inoculants, pest management, productivity analysis, stochastic frontier

JEL Classifications: D24, Q13, Q16

Disease management in crops worldwide is heavily dependent on application of synthetic pesticides for pathogen and insect control. However, excessive application of pesticides contributes to the development of pest resistance leading to higher chemical input use. At the same time, strict environmental legislation such as the Federal Insecticide, Fungicide, and Rodenticide Act, the Food Quality Protection Act, and the Federal Food, Drug, and Cosmetic Act can discourage the use of chemical inputs (White, 1998; EPA, 2012; FDA, 2012). Moreover, there is a concern about increasing concentration of international agricultural chemical input markets (Just, 2006; Fernandez-Cornejo and Just, 2007; Marcoux and Urpelainen, 2011). As a result, producers are seeking alternative pest and weed control technologies.

In this context, biological control products offer an attractive alternative to synthetic pesticides. Biological control agents (BCAs), by a broad definition, are living organisms or natural products derived from them that can be used against plant-damaging agents. Over the last two decades, biological control of plant pathogens has emerged as a viable pest (insect and disease) control strategy (Harman et al., 2010; Singh, Pandey, and Singh, 2011). Microbial inoculants (MIs) are a technology that can be used as a biofertilizer and/or as a BCA. The MI technology includes viruses, bacteria, and fungi whose application holds a promise of reducing the adverse effects associated with traditional chemical input use (Berg, 2009). Because all the MI agents used in apple production are

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registered as a BCA and not biofertilizer, for the present purpose, MI is strictly defined as a BCA.

Quantifying economic impacts of the MI is necessary for the assessment of potential economic viability of the MI as a substitute for chemical pesticides. In agronomic research, the impact of biological control is assessed through cost–benefit analysis using experimental data and farm budgets. Empirical research in applied economics uses historical farm-level data in estimating production, cost, or profit functions. In this study, a pesticide use function and different production functions, including a stochastic frontier, are estimated. The chosen crop is apples because the technology is already being adopted by producers and because, according to the U.S. Department of Agriculture Pesticide Data Program, apples rank as the most contaminated fruit and vegetable produce (USDA, 2013).

The rest of the article is structured as follows. The "Background" section briefly reviews MI and pesticide use in apple production. The "Data" section describes the data and summarizes the use of different biological control products. Models used in empirical estimation are described in the "Methodological Framework" section. Results are discussed in the following section. The last section concludes.

Background

Apples' major insect pest is codling moth. Apples also host over 70 infectious diseases, fireblight, scab, and powdery mildew being the major ones (Ohlendorf, 1999). The primary means of controlling these insect and pathogen threats is synthetic pesticide application. However, a holistic approach, using tools such as biological control, may reduce pesticide application rates allowing application of only selective chemicals.

Integrated pest management (IPM) is a holistic approach that integrates several methods of insects and diseases management. IPM is formally defined as "an effective and environmentally sensitive approach to pest management that relies on a combination of common-sense practices. IPM programs use current, comprehensive information on the life cycles of pests and their interaction with the environment. This information, in combination with available pest control methods, is used to manage pest damage by the most economical means, and with the least possible hazard to people, property, and the environment" (EPA, 2013). The use of resistant rootstocks and scions, fungicides, bactericides, BCAs, environmental modification, and site selection are some of the means used to control apple damage factors (Grove et al., 2003).

According to the International Biocontrol Manufacturers' Association, BCAs can be divided into three categories: macrobial (insects, mites, nematodes, other nonmicrobial organisms), microbial (virus, fungi, bacteria), and biorational (natural products and semichemicals) (Guillon, 2008). However, according to several pest management researchers (Copping and Menn, 2000; Chandler et al., 2008), genetically modified organisms (GMOs) are recognized as a separate BCA category in some countries such as the United States (this association will be useful later in the article). BCAs are used in two types of agriculture. The first one is organic farming where using chemical inputs is not permitted. The second, which is the focus of this study, is integrated crop production programs. This type of agriculture includes IPM strategies focusing on reduction in pesticide use and resulting in improved environmental and food quality. BCAs can be applied together with chemicals, either in rotation to reduce the possible development of pathogen resistance or in an IPM strategy with the goal of minimizing the use of synthetic pesticides.

MIs are control agents of agricultural pests developed from microbial natural enemies in the bacteria, fungi, and viruses. Only a very small fraction of the known potential MIs have been investigated for practical use (Chandler et al., 2008). Although widespread adoption of the microbial control agents is still facing some technical and ecological challenges, this technology is already an important part of the IPM. According to Bailey, Boyetchko, and Längle (2010), there are approximately 225 microbial biopesticides being manufactured in the Organization for the Economic Development and Cooperation countries. Currently, 53 microbial biopesticides are registered in the United States. On the other hand, the synthetic pesticide market has been declining slowly and continuously after reaching a volume of $34 billion in 1995 (Guillon, 2008). In 2005, the volume of synthetic pesticide sales was only $26.1 billion, in part as a result of the increased adoption of IPM practices (Thakore, 2006). Although there are more than 1,000 different products available from more than 350 manufacturers worldwide, BCAs accounted for only approximately 2.5% of the plant protection input market in 2005, amounting to approximately $588 million at end-user prices (Guillon, 2008). However, the use of BCAs has been growing at an annual rate of 10% reaching 4.25% of the pesticide market in 2010 (Ongena and Jacques, 2008; Bailey, Boyetchko, and Längle, 2010).

MIs represented 30% of the total sales of biocontrol pesticides in 2006, of which bacteria accounted for 75%. The total value of sales for MI was $205 million. Most of the bacterial strains exploited as biopesticides belong to the genera *Agrobacterium, Bacillus*, and *Pseudomonas* (Fravel, 2005). *Bacillus thuringiensis* (Bt), specifically devoted to insect pest control and also used in crop genetic modifications, accounts for more than 70% of total biocontrol sales (Thakore, 2006; Ongena and Jacques, 2008; Bailey, Boyetchko, and Längle, 2010).

In 2006, the EPA banned the use of a pesticide called Azinphos-Methyl (AZM) in apple production since September 30, 2012. Although AZM provides important pest control benefits to apple and other crop growers, it can also potentially harm farm workers, pesticide applicators, and water ecosystems (Cassey, Galinato, and Taylor, 2010). This regulation is expected to have significant economic consequences and bring changes in apple production practices.[1] In addition, in 2011, the National Organic Standard Board voted to phase out the antibiotics streptomycin and oxytetracycline by 2014, which are the primary tools used by conventional and organic apple producers to prevent fireblight (Washington State University, 2012).This may be the niche opportunity for the MI technology in apple production.

Data

The USDA's Agricultural Resource Management Survey (ARMS) data on apple production were used for this study. This survey contains information on production practices, inputs and costs, and financial performance of the U.S. farm households. Data on most direct inputs and farm characteristics come from the Phase II part of the survey, whereas other variables such as yields and area harvested come from the Phase III part of the survey. Data from the latest commodity survey of apple production in 2007 were used in the analysis. The ARMS data have unique characteristics that make it well suited for this research. First, the data set covers more than 90% of the acreage of targeted commodities. Second, it uses a stratified random sample in which each farm represents a known number of similar farms in the population based on their probability of being selected (weights). Using this statistic, the ARMS sample can be expanded to reflect the targeted population. Lastly, the enterprise costs-of-production data contain sufficient detail about specific inputs to isolate the seed and pest control costs used to produce a given commodity.

Seven states were represented in the survey: Michigan, Oregon, New York, Pennsylvania, North Carolina, California, and Washington. Washington was used as the base (benchmark) for its continuous and successful production history and because it is the state with the highest total production (Economic Research Service, U.S. Apple Statistics, ERS-USDA, 2012).

Only conventional (nonorganic) farmers are considered in this study as the intent is to estimate the supplemental effect of MI on pesticide use.[2] The use of biological control is

[1] For example, AZM has been the pesticide most used by Washington State apple growers since the late 1960s and, in 2008, 80% of Washington apple growers used AZM primarily to control codling moth (Cassey, Galinato, and Taylor, 2012).

[2] Pesticides refer to chemical insecticides and fungicides. Although insecticides and fungicides have different impacts on outputs, we pool them as MIs because they have the potential to substitute both.

defined as "1" if the farmer was using the technology and "0" otherwise in the "Pest Management Practices" section of Phase II of the survey. Although we would prefer to use a quantitative measure of the MI applications, the small percentage of farmers using this technology in 2007 makes a dummy variable more appropriate. In the sample of 547 conventional farms, 197 farms were using on average three MI products, from which the main ingredient included one of the following: Granulovirus, Bt, *Bacillus subtilis*, *Bacillus pumilus,* and *Thricoderma* sp. All of these products are strictly used for biological control. Figure 1 shows the percentage represented by each biological agent, from which 96% fall into the MI definition.

MI provide good resistance to different varieties of insects and diseases, caused by either bacteria or fungus, in apples. The most common microbial pesticide is the Granulovirus used against codling moth (*Cydia pomonella*) and Bt proven to work against many insects (Ohlendorf, 1999). Regarding the others, *Bacillus subtilis* and *Bacillus pumilus* provide mild resistance against fireblight and some other diseases (Peighamy-Ashnaei et al., 2008; Sundin et al., 2009). It is important to mention that the MI technology does not completely eliminate the need for chemical pesticides because it is ineffective against some insects and diseases.

Table 1 presents summary statistics for adopters and nonadopters. Pesticide includes

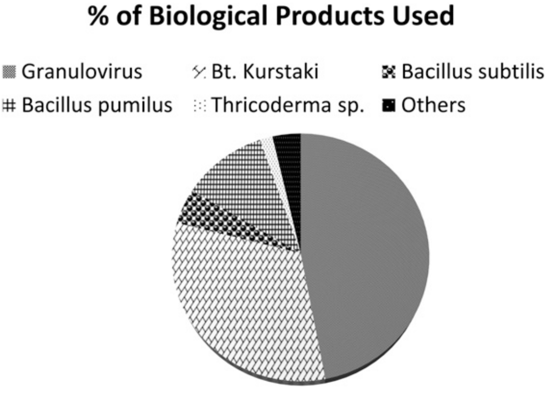

Figure 1. Biological Control Distribution by Type

insecticide and fungicide applications net of any biological control product. Contrary to the previous findings based on experimental data (Cross et al., 1999; Peighami-Ashnaei et al., 2009), the use of pesticides on plots with MIs is 25% higher than on plots without it. This positive relationship could be explained by more intensive pest management practices of the adopters and corroborated by the adopters' higher sales volumes. The difference in sales between adopters and nonadopters (38%) is much more pronounced than the difference in yields suggesting possible higher quality attributes including visual appearance, which, for apples, is achieved by increased chemical application rates. The data also show that the adopters have less experience, which fits some of the paradigms about biological control adoption constrained by institutional and social barriers (Peshin and Dhawan, 2009).

Methodological Framework

To determine the impact of the adoption of the MI technology in apple production, we estimate a pesticide use (demand) function and a production function. The production function estimates the output enhancing effect of the MI technology previously indicated in field trials (Cross et al., 1999; Ballard, Ellis, and Payne, 2000; Cossentine, Jensen, and Deglow, 2003; Peighami-Ashnaei et al., 2009). Pesticide impacts on apple production have been measured before (Babcock, Lichtenberg, and Zilberman, 1992; Chambers and Lichtenberg, 1994; Lichtenberg, 1997; Hubbell and Carlson, 1998; Roosen, 2001). However, at the time of writing this article, we did not find references to economic studies assessing the impact of the MI technologies using production data. At the same time, there is voluminous empirical literature on transgenic (GMOs) crop adoption and production impacts. Because MI and transgenic Bt crops have similar properties (Bt crops produce proteins toxic to larvae of some insects species, thus substituting for chemical insecticides), we try to fill the gap in empirical research on the BCA impacts using the methodology from this literature (Huang et al., 2002; Qaim, 2003; Pemsl, Waibel, and Gutierrez, 2005; Qaim and

Table 1. Summary Statistics for Apple Production

	(a) Using MI			(b) Not using MI		(c) All farms	
Variable	Mean		SE	Mean	SE	Mean	SE
Experience, years	24.7		1.5	27.1	1.6	26.0	1.1
Pest pressure	14.9		0.6	14.7	0.6	14.8	0.4
Pesticide, lbs/acre	79.9	*	11.7	63.8	3.2	70.6	5.3
Value of sales, $/acre	3,360.7	*	377.1	2,432.2	327.2	2,825.8	243.5
Yield, lbs/acre	26,172.2		1,445.2	25,091.8	1,997.8	25,549.7	1,302.2
No. of observations	189			348		537	
Population	7,104			9,657		16,761	

* Significantly different from mean value on nonadopter plots at 10% level.
SE, standard error.

de Janvry, 2005; Shankar and Thirtle, 2005; Shankar, Bennett, and Morse, 2008).

Pesticide Use (demand) Function

As stated before, MI does not completely eliminate the need to spray chemical pesticides to avoid pest damage. Thus, although controlled field experiments suggest that the MI technology substitutes chemical pesticide use, we do not expect it necessarily to be the case for actual production because the practices differ in a number of respects.

To investigate the relationship between MI adoption and pesticide use, a pesticide demand function similar to Huang et al. (2002), Qaim (2003), and Qaim and de Janvry (2005) is specified[3]:

$$\text{Pesticide} = f(\text{price, MI adoption, H, pressure, state dummies}) \quad (1)$$

where Pesticide is the pesticide application in pounds per acre and MI is the adoption dummy variable. The price of pesticides was obtained by dividing pesticide expenditure by quantity per farm. H is a vector of farm characteristics; pressure is an index (actually two indices: insect pressure and disease pressure) reflecting the level of pest infestation before spraying decisions.[4] The state dummies proxy for different agroclimatic conditions in different states.[5]

Production Function

The net yield effect is estimated using a modified production function approach. Following the concept proposed by Lichtenberg and Zilberman (1986), inputs in agricultural production can be divided into two main categories: standard factors of production (e.g., land, labor, capital, etc.) and damage control agents (e.g., insecticides, fungicides, biological control, etc.). Damage control agents are different in the sense that they enhance productivity only by preventing output losses. This specific contribution of damage control agents is accommodated by specifying output as a combination of two components: potential damage-free output and losses caused by damaging agents. The losses can be mitigated (abated) by using damage control inputs. Like in previous research

[3] This pesticide demand function was mainly specified as an instrumental variable (IV) approach to address the potential endogeneity of pesticides on the production function in the second stage. As long as the set of variables explains pesticide use but not yields, the IV produces unbiased estimation results. The instruments in this equation are price and pest pressure. In addition, after previous research, we have included some control variables such as experience and location dummies used in both functions.

[4] Two indices, one for insects and one for diseases (both with five subcategories), were used. These two indices range from 5 (low pressure) to 15 (high pressure). The variable "pest pressure" listed in the summary statistics is a summation of both.

[5] Possible income effects of the MI technology adoption are ignored as a result of the realistic assumption of seasonal input borrowing and substitution between the MI and chemical pesticides indicated by field trials.

(Babcock, Lichtenberg, and Zilberman, 1992; Chambers and Lichtenberg, 1994; Huang et al., 2002; Qaim, 2003; Qaim and de Janvry, 2005), we use the concept of a damage control function, g(Z), which is linked to the production function in a multiplicative way:

$$\text{(2)} \quad Y = f(X)\, g(Z)$$

where Y represents output and X includes labor, fertilizers, other production inputs, farm-specific factors affecting yields and location-specific factors (state dummies). The abatement function of damage control agents, g(Z), possesses the properties of a cumulative probability distribution and is nondecreasing in Z. g(Z) = one implies full damage control (no crop yield losses resulting from pest-related problems with a certain high level of control agent), whereas g(Z) = zero implies complete crop destruction by pest-related damage.

For f(X), we assume the Cobb-Douglas functional form, whereas different functional forms can be assumed for g(Z) and the specification can be crucial for parameter estimation results (Babcock, Lichtenberg, and Zilberman, 1992; Carrasco-Tauber and Moffitt, 1992; Fox and Weersink, 1995). Exponential (equation [3]) and logistic (equation [4]) specifications are used because they generally represent the pest abatement relationship quite well:

$$\text{(3)} \quad g(Z) = 1 - \exp(-\alpha_0 - \alpha_1 \text{Pesticide} - \alpha_2 \text{MI})$$

$$\text{(4)} \quad g(Z) = [1 + \exp(\mu - \alpha_1 \text{Pesticide} - \alpha_2 \text{MI})]^{-1}$$

where pesticide is expressed in pounds per acre and MI is the binary variable. The parameter α_0 in equation (3) is interpreted as natural control (for example, the activity and pest-reducing capacity of natural enemies/competitors present in the orchard), whereas μ in equation (4) is interpreted as fixed damage (the damage without any pest/disease risk management). The linear version of equation (2) is:

$$\text{(5)} \quad \begin{aligned} \text{Log}(Y) &= a + \sum \beta i\, \text{Log}(X) + \sum \beta i\,(H) \\ &\quad + \text{Log}(g[Z]) + \varepsilon \end{aligned}$$

H is a vector of controls for farm and location characteristics. In addition, a standard Cobb-Douglas production function treating pesticide and biological control as conventional production factors is estimated for comparison purposes.

A potential problem in estimating crop production functions is that pest control inputs tend to be correlated with the error term because pesticide applications are responses to pest pressure that vary by specific climate conditions and other unknown or nonmeasurable factors captured in the disturbance. To correct for possible endogeneity, we use two-stage least squares for the pesticide use (equation [1]) as the first stage and the production function (equation [2]) using fitted pesticide use values as the structural equation.[6] A number of control variables such as farmer's characteristics and the state dummy variables are included in both the yield and pesticide use equations. This specification passes the Ramsey RESET test for omitted variables. The production functions are also tested for multicollinearity using variance inflation factor and corrected for heteroscedasticity using robust standard errors. The Chow test is performed to confirm that the two groups can be pooled together.

In addition to the Cobb-Douglas and the integrated damage control production functions, a stochastic production frontier (SPF) is estimated. In contrast to a regular production function, SPF allows for inefficiency because it does not assume that all farmers are producing on the production possibilities frontier. The SPF can be interpreted as the technological constraint for each farming system. The distance from the frontier indicates a farm's relative performance or technical efficiency. The general form for an SPF model is

[6] In theory, other inputs could be endogenous as well. However, pesticides are more likely to present this econometric issue. MI application, in particular, has the potential to be an endogenous variable. However, MI adoption is currently associated more with the area of commercialization of the products and more long-term production and output quality-related concerns. The EPA requires each different variation of BCA to be registered individually in each state. Thus, we assume away significant endogeneity.

$$(6)\qquad Yi = f(X_i;\beta)\exp\{v_i\}TE_i$$

where Yi and Xi are output and input vectors of producer i. Deterministic production frontier f(Xi; β) multiplied by $\exp\{v_i\}$ capturing the effects of statistical noise represents the stochastic production frontier. $TEi = \exp\{-u_i\}$ is the i's output-oriented technical efficiency that provides a measure of the shortfall of observed output from maximum feasible output ($TE_i \le 1$, $u_i \ge 0$). The log-linear Cobb-Douglas specification of the model is

$$(7)\qquad \mathrm{Log}\,Yi = \beta_0 + \sum \beta_n \mathrm{Log}\,X_{ni} + v_i - u_i$$

where $v_i \sim \text{iid } N(0, \sigma_v^2)$, $u_i \sim \text{iid } N+(0, \sigma_u^2)$, and v_i and u_i are independent. The assumption on u can be modified to $u_i \sim \text{iid } N+(\mu, \sigma_u^2)$ where μ is the mode of the normal distribution and is truncated below at zero. The Normal–Truncated Normal model provides a more flexible representation of the efficiency pattern in the data (Kumbhakar and Lovell, 2000; Coelli, Rao, and O'Donnell, 2005). Point estimates for technical efficiency of each producer can be obtained by means of

$$(8)\qquad TE_i = E[\exp\{-u_i\}\,|\varepsilon_i]$$

where $\varepsilon_i = v_i - u_i$.

The basic stochastic frontier model analysis does not accommodate endogeneity of regressors resulting in biased estimates. However, endogeneity does not bias estimates of technical efficiency with stochastic distance functions (Kumbhakar and Lovell, 2000), validating the use of technical efficiency estimates.

Results

Table 2 shows the results of the pesticide use function estimation. The Cobb-Douglas model produced a significantly better fit. Although all the coefficients have the expected signs in both specifications, curiously, the MI adoption dummy has a positive and significant coefficient contradicting some previous studies on BCAs (Huang et al., 2002; Pemsl, Waibel, and Gutierrez, 2005; Qaim and de Janvry, 2005).

This unexpected result might fit some established paradigms about the use of biocontrol agents like, for example, "the more a grower is willing to gamble, the better prospect he has of accepting the idea of biological control" and "prevention treatments are basically an insurance policy" (Peshin and Dhawan, 2009). In other words, adoption of biological control agents at its initial stage is "insured" by increased use of conventional damage control inputs. This is corroborated by the low price elasticity of pesticide use (–0.54). The relationship between adoption

Table 2. Pesticide Use Function Estimation

	Logarithmic			Linear		
	Coefficient		t Value	Coefficient		t Value
Microbial inoculant (dummy)	0.22064	***	2.79	16.82674	*	1.92
Log price	–0.53831	***	–7.10	–20.56438	***	–5.10
Pest pressure insects (index)	0.53821	***	2.95	3.67453	*	1.62
Pest pressure diseases (index)	0.00454		0.27	–2.27674		–1.38
Log farm size	0.51135	***	8.19	22.99091	***	3.68
Experience	–0.00869	***	–3.35	–0.39372		–1.42
Michigan	–0.29136	*	–1.79	–21.45761	*	–1.76
Oregon	–0.18341		–1.17	–8.69145		–1.49
New York	–0.40624	**	–2.12	–25.12487	*	–1.75
Pennsylvania	–0.37066	***	–3.61	–26.73133	**	–2.07
North Carolina	–0.65578	***	–4.96	–17.12455	*	–1.69
California	–0.77040	***	–3.43	–13.98782		–1.17
Constant	21.94957	***	4.23	1012.67112		1.52
No. of observations	525			525		
Population	15,953			15,953		
R^2 adjusted	0.5365			0.2269		

***p value < 0.01, ** < 0.05, * < 0.1.

and pesticide use may also be corroborated by the fact that, especially in areas with high grower concentration, pesticides are usually marketed on a continuous basis and bundled with consulting provided by chemical suppliers, which may slow down adoption and prevent the associated reduction in pesticide application rates.[7]

Farm size is positively associated with pesticide use, which probably reflects the higher intensity of larger operations. Insect pest pressure is positive and significant as expected. A year of farming experience reduces pesticide use by 0.87%, possibly indicating persistence of certain cultural paradigms. Dummy variable coefficients show that per-acre use of pesticide is the highest in Washington, the biggest apple-producing state.

Table 3 shows results of the production function estimation. Overall, MIs have a positive impact on output, but the magnitude and significance vary by the model.

In the Cobb-Douglas production function, the use of MI technology increases apple yields, *ceteris paribus*, by approximately 13% per acre at the variables' mean values, which agrees with the summary statistics and corroborates the findings by Qaim and de Janvry (2005), Qaim (2003), and Huang et al. (2002) who found that the use of Bt cotton increases yields by 507 kg/ha in Argentina, by 75% in India, and by 15% in China. Chemical pesticides also contribute to higher yields. For a 1% increase in the amount of pesticides used, the yield increased by 0.13%. The elasticity with respect to labor is 0.089%. The impact of nitrogen and potash fertilizers is positive but negative for phosphate suggesting possible overuse. Production elasticity with respect to area (acres) harvested is small suggesting constant returns to scale. The only states that are more (less) productive than Washington are Pennsylvania and North Carolina.

Results from the integrated damage control model are similar and provide a slightly better fit and higher significance of the damage control inputs under the logistic specification. Both MI and regular pesticides increase yields by improving crop protection. The MI technology is effective in helping to reduce the damage from pest infestations and thus keeping yields higher than they would have been without the adoption.

Without any pest control inputs and under the logistic damage control specification, average crop damage would have been approximately 57% of the mean yield. The marginal physical product of pesticides, obtained by taking a partial derivative at the mean input values, is 0.119 and 0.138 with and without the use of the MI, which agrees with the nature of the technology and with previous studies on adoption impacts (Huang et al., 2002; Qaim, 2003; Pemsl, Waibel, and Gutierrez, 2005; Qaim and de Janvry, 2005). However, adoption of the MI technology increases damage control over the whole range of possible pesticide application levels, which is illustrated by the plots in Figure 2 constructed using the estimates and average variable values.

The significance of the MI technology adoption is less than expected possibly because adoption at its initial (current) stage is influenced by other factors that are not captured in our data. These factors include the spatial contagion effect (impact of neighbors), extension efforts (some areas are reached better), and promotions by the supplier.

The damage control specification increases output elasticity with respect to acres harvested from 0.08% to 0.16%, which confirms Lichtenberg and Zilberman's (1986) finding that traditional Cobb-Douglas production functions tend to underestimate the impact of direct inputs. Irrigation expenditure is not significant throughout, possibly as a result of the climate and the fact that apple trees are less dependent on rainfall.

Technical efficiency estimates as shown in Table 4 indicate that adopters of the MI technology have 2.52% higher efficiency rates than nonadopters whose average technical efficiency score is 60%. Although the difference is small, this might suggest self-selection in a promising technology adoption, assuming more efficient producers are the first to see the opportunity.

[7] We thank an anonymous reviewer for pointing this out.

Table 3. Estimates of the Production Function

	Cobb-Douglas Basic			With Exponential Damage			With Logistic Damage		
	Coefficient		t Value	Coefficient		t Value	Coefficient		t Value
Pesticide	0.1255	*	1.77						
Experience	–0.0013		–0.56	–0.0003		–0.13	–0.0003		–0.12
Trees (expenditure on pruning)	–0.0051		–0.88	–0.0116	**	–2.18	–0.0121	**	–2.27
Labor	0.0886	***	4.99	0.0774	***	6.55	0.0786	***	6.73
Irrigation	–0.0058		–0.96	–0.0096		–1.33	–0.0093		–1.29
Fuel	–0.0032		–0.64	–0.0038		–0.70	–0.0039		0.70
Bees (expenditure on bee hives)	0.0066		1.03	–0.0008		–0.13	–0.0009		–0.13
Nitrogen	0.0183		0.79	0.0263	*	1.79	0.0265	*	1.80
Potash	0.0410	*	1.89	0.0293		1.60	0.0285	*	1.65
Phosphate	–0.0741	**	–2.28	–0.0755	**	–2.58	–0.0747	**	–2.55
Microbial inoculant (dummy)	0.1208	*	1.71						
Acres harvested	0.0762	***	2.64	0.1626	***	6.88	0.1649	***	7.01
Michigan	–0.0077		–0.07	–0.0091		–0.07	0.0111		0.09
Oregon	–0.4016		–1.58	–0.4059	***	–2.62	–0.4072	***	–2.63
New York	0.1924		1.61	0.1868		1.43	0.2058		1.58
Pennsylvania	0.3973	***	3.53	0.3693	***	2.64	0.3904	***	2.82
North Carolina	–0.8564	***	–3.86	–0.8090	***	–3.10	–0.7913	***	–3.04
California	–0.1268		–0.47	–0.4398	***	–3.00	–0.4279	***	–2.92
Constant	10.9300	**	2.39	9.6541	**	2.29	9.6114	**	2.28
Damage control function									
Constant (α_0, μ)				0.5346	***	4.02	0.2845	*	1.65
Pesticide				0.0108	*	1.91	0.0154	**	2.56
Microbial inoculant (dummy)				0.2106		1.46	0.3787	*	1.93
No. of observations	510			525			525		
R^2 adjusted	0.3654			0.3739			0.3751		
Population	15,497			15,953			15,953		

*** p value < 0.01, ** < 0.05, * < 0.1.

Alternatively, this might indicate more efficient pest management using MI.

Apple production is more technically efficient in the states of Washington, Pennsylvania, Michigan, and California by at least 3% compared with New York and North Carolina. An interesting finding is that in those states where efficiency rates are lower than average, nonadopters have relatively higher efficiency rates. This may be attributed to differences in agricultural practices or institutional and environmental factors. but the causal relationship remains unclear.

Because the data are insufficient for specifying a profit model (the ARMS data lack input prices including MI and the spatial price variability is likely low), average impact of the MI technology use on farmers' returns was calculated using the data and the estimates of the MI impact on productivity. which, using average yields and the MI coefficient, indicate an average yield gain of approximately 3,000 lbs/acre. Using a season average grower apple price of $0.288/lb for fresh apples (ERS data on processed apples for 2007) results in extra gross income of approximately $840. Individual producer cost of MI products was estimated at $558 per acre using per acre application prices (expenditures) for the products actually used by the

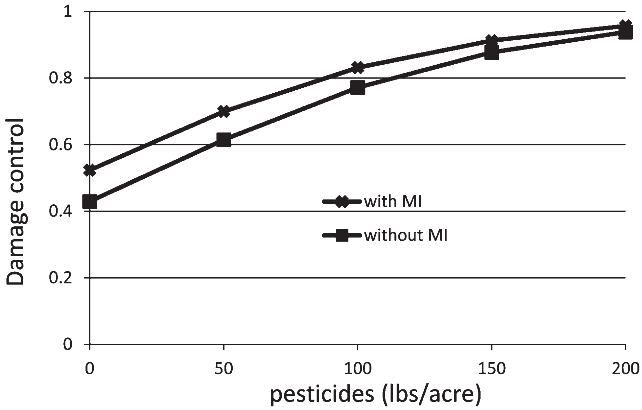

Figure 2. Microbial Inoculant (MI), Pesticides, and Damage Control Relationship

197 adopters in the sample.[8] The net revenue from applying microbial inoculants was thus calculated at approximately $282 per acre per growing season (assuming there is no extra labor or machinery costs for applying the product).

Conclusions

This article analyzes the impact of applying a specific type of biological control agent called MIs on productivity and pesticide use in conventional (nonorganic) apple production in the United States using the ARMS survey data. The MI technology is an IPM approach that is similar to the insect resistant transgenic technologies (GMOs) in agriculture but does not carry the environmental and health concerns posed by the latter, which holds promise for its adoption in the future. It was adopted by 36% of the U.S. apple producers in 2007. The technology has the potential of reducing pest damage and increasing yields without the associated negative health and environmental impacts associated with pesticide and other chemical input use (Fravel, 2005).

Estimation of a pesticide use function shows that adoption of the MI technology increases the use of pesticide inputs, which, although contradicting some previous findings, conforms to observed paradigms regarding producer attitudes toward production risk and resulting chemical use, i.e., that BCAs are often perceived as "insurance." The available cross-sectional data do not allow estimation of causal relationship between pesticide use (pest pressure) and MI adoption.

Estimation of different types of production functions with a separate damage control component and controlling for pesticide use endogeneity shows that the MI technology significantly increases yields and reduces the marginal productivity of pesticides. Estimation of a stochastic production frontier shows higher technical efficiency of the MI adopters except for the states with the lowest average efficiency in which nonadopters have higher efficiency rates. The states with the highest rates of technical production efficiency are Washington, Pennsylvania, and California. The impact of adoption on producer income depends on the productivity impacts, output prices, and the costs of biological control products. Our estimates using calibration data suggest a net gain of $282 per acre per season. According to this study, MI can complement, rather than substitute, agricultural chemical use easing compliance with regulations and positively impacting yields.

It remains to be seen whether MIs are going to be as successful as genetically modified crops were 15 years ago. Our results suggest some similarities between the two technologies in production impacts and adoption patterns. MI

[8] The products are: Granulovirus products (used for codling moth), Bt products (used for different insects), and *Bacillus pumillus* and *Bacillus subtillis* (used for fireblight and powdery mildew). Per-acre price was calculated by adjusting the price of a container of known volume by the recommended application quantities and times per season.

Table 4. Average Efficiency by Technology Use and State

	All Farms	Adopters	Nonadopters	Efficiency Gains
All farms	0.6085	0.6254	0.6002	0.0252
California	0.6170	0.6616	0.5986	0.0630
Michigan	0.6186	0.6287	0.6140	0.0147
New York	0.5826	0.5725	0.5862	–0.0137
North Carolina	0.5829	0.5018	0.5909	–0.0891
Oregon	0.6104	0.6843	0.5661	0.1182
Pennsylvania	0.6174	0.6204	0.6162	0.0042
Washington	0.6198	0.6236	0.6157	0.0079

increases output and its adoption seems to reduce production risks. However, greater confidence requires establishing causal relationships between adoption impacts and producer characteristics. Analysis of panel data that includes spatial variables will improve our understanding of adoption dynamics and market potential of the MI technology, which is still in its infancy stage.

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