Stochastic Frontier Analysis of Biological Agents (Microbial Inoculants) Input Usage in Apple Production

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Abstract

This paper analyzes the effect of Microbial Inoculants (MI) Technology over pesticide and yields in apples using 2007 farm data. The results show that pesticide usage is not reduced by MI applications; however, there is a significant positive effect over the outputs. Farmers' efficiency rates are on average 37%.

Introduction

Currently, disease management in crops worldwide is heavily dependent upon application of synthetic (chemical) pesticides for pathogen and insect control. However, the excess application of pesticides can enhance the development of pest resistance, thus requiring more chemicals or increasing the damage of pests. Also, stricter regulations compromising yields for environmental objectives discourage the use of pesticides. As an example, regulations in the United States are based almost entirely on the direct effects on health and environment (White, 1998). Moreover, chemical pesticides' prices have been increasing as fuel prices have been increasing and because big portion of the market power is shared only by few big transnational producers who are becoming the only suppliers (Marcoux and Urpelainen, 2011; Fernandez-Cornejo and Just, 2007). All of this works against farmer's profit maximizing objectives and makes them to look for alternatives that can keep up with higher yields.

In the last years, global demand for more environmentally friendly products and sustainable production systems has been increasing. In this context, biological control products offer an attractive alternative to synthetic pesticides. According to Pal and Gardener (2006) "Biological control refers to the purposeful utilization of introduced or resident living organisms, other than disease resistant host plants, to suppress the activities and populations of one or more plant pathogens”

Over the last two decades, biological control of plant pathogens has emerged as a viable disease control strategy (Harman et al., 2010; Singh et al., 2011). Microbial inoculants (MI) is a type of biocontrol agent that includes bacteria and fungi, representing an environmental friendly approach to reduce losses due to pest and diseases or showing as an alternative to chemical pesticides (Lugtenberg et al., 2002). Impact assessments of biological control are measured by cost-benefit analysis in an ex-ante situation but, for ex-post analysis, a production function, that can have an integrated damage control, is a standard procedure in agricultural production economics. The chosen crop is apples as there are already some products being applied and because according to the United States-based Environmental Working Group (EWG), apples rank as the most contaminated fruit and vegetable produce (Lloyd, 2011; Bagnato, 2011)

The objectives of this study are to quantify the contribution of MI and other production factors to the 2007 U.S. apples yields, and to estimate the effects of MI usage over pesticide usage.

Data basis

USDA’s 2007 Agricultural Resource Management Survey (ARMS) data on apple production was used for this study. This survey contains information on the, production practices, inputs and costs, and financial performance of America’s farm households. Most of the data come from the Phase 2 part of the survey. Only conventional (non organic) farmers were considered as intend was estimate the complementary and/or supplemental effect over pesticides. Under the “pest management practices” section of the production practices and costs reports (phase 2) of the survey, an item referring to biological control was used as the variable of interest. In the sample of 547 conventional farms, 197 farms were using one or more biological control products, from which the main ingredient included one of the following: Granulovirus, *Bacillus thuringensis, Bacillus subtilis, Bacillus pumilus* and *Thricoderma sp*. Figure 1 shows the percentage represented by each biological agent, from which, 67% fall into the MI definition.

[Place Figure 1 Approximately Here]

MI provides good resistance to different varieties of insects and diseases for apples compared to others biological agents used in this study. For example, the Granulovirus is only used against Codling moth *(Cydia pomonella),* but *Bacillus thuringensis* has been proved to work against Codling moth, Apple pandemis, Leafrollers, Western tussock moth, Velvetbean caterpillar and Green fruitworm (California, 1999). *Bacillus subtilis* has been proven to work against Fire Blight, Botrytis, Sour Rot, Rust, Sclerotinia, Powdery Mildew, Bacterial Spot and White Mold (Peighamy-Ashnaei *et al.*, 2008; Sundin *et al.*, 2009). However, there are many other pest and diseases to which MI agents do not provide resistance; Therefore, MI does not completely eliminate the need to use chemical pesticides. For easiness of the study, from now on MI will refer to all biological agents used in the data (as Granulovirus was often combined with an MI agent).

Seven states were represented in the survey: Michigan, Oregon, New York, Pennsylvania, North Carolina, California and Washington, the last one used as the base. Washington was used as the base for its continuous and successful history of apple production.

Data analysis and framework

Effects of MI on pesticide application

As a first step, the summary statistics of those farmers using and not using the technology are compared to have a quick look of what might have been happening. The variable pesticide is only including insecticide and fungicide applications, herbicides were not took into account as they fall into other category. In order to confirm the findings, a more precise quantification was needed. A Cobb-Douglas type functional form was estimated using OLS regression to estimate the technology's effect over the pesticide use. This was calculated using plot and farmer characteristic. The amount of pesticide (pest) in pounds per acre can be expressed as:

$$\text{Log (Pest)} = \text{Log (A)} + \sum \beta_i \text{ Log (X)} + \sum \beta_i \text{ Log (VS)} + \beta_1 \text{ (MI)} + \sum \beta_2 \text{ (K)} + \varepsilon \qquad (1)$$

Where A is the intercept, X is a vector of direct production inputs, VS is the value of sales per acre. In this study, value of sales per acre is used as a proxy for yields per acre. With cross-sectional data, using a nominal output measure (revenue) or a physical production output measure makes very little difference as it was stated by Mairesse and Jaumandreu (2005). MI is a dummy variable which takes the value of one for MI plots and zero otherwise[1]. Lastly, K is a vector of other determining factors such as experience, expenditure on pesticide over pesticide (as proxy of price), pest pressure and a state area variable (dummy) as proxy for the different agro climate conditions found in these areas.

Productivity and damage control

A production function or frontier is defined as the specification, given an available technology, of the maximum amount of output possible to produce given a certain quantity of inputs and combinations. It measures the effect of each exogenous variable over the quantity produced.

[1] It would have been advantageous to use a quantitative measure of the MI applications but the AMRS survey data, the most comprehensive data available to us, only contains a categorical measure of MI use.

Different types of production functions are estimated to measure MI impact over the output production. First, a Cobb-Douglas specification is used, which in general is the standard approach for a production function. We estimate the following relationship:

$$\text{Log (VS)} = \text{Log (A)} + \sum \beta_i \text{ Log (X)} + \beta_1 \text{ (MI)} + \sum \beta_i \text{ (P)} + \varepsilon \qquad (2)$$

Where VS is the value of sales per acre, A is the intercept, X is a vector of direct production inputs, MI is the microbial inoculants dummy variable and P is a vector of experience and area variables.

In agricultural production, inputs can be divided into 2 main categories: standard factors of production (e.g. land, labor, capital, etc.) and damage control agents (e.g. pesticides, herbicides, and biological control). The damage control agents enhance productivity indirectly by preventing output loses. Thus, a damage control function needs to be integrated in a production function as inputs cannot be treated in the same way. In the analysis of pesticide productivity, the use of a standard Cobb-Douglas function is criticized for treating pesticide as a yield increasing production factor and not capturing knowledge about physical and biological processes of pest control agents. Lichtenberg and Zilberman (1986) explain that using a Cobb-Douglas functional form results in overestimation of productivity of damage control inputs, while productivity of other factors will be underestimated. To address this problem they introduce the concept of damage control functions. They propose using a separate damage control function G, which is linked to the production function in a multiplicative way.

$$Y = f\ (X)\ g\ (Z) \qquad (3)$$

Where X denotes normal inputs, and Z pest control agents. g (Z) possesses the properties of a cumulative distribution function, with values defined in the (0, 1) interval. Thus, f(X) is the potential maximum yield to be obtained with zero pest damage or maximum pest control.

For f (·) we use the same Cobb-Douglas functional form as before, whereas for g (·) different functional forms can be assumed and specification can be crucial for the parameter estimation results (Carrasco-Tauber and Moffitt, 1992; Fox and Weersink, 1995). But, since up until now there is no consensus on which specification best suits the purpose, a logistic specification is used as it generally represents the pest abatement relationship quite well and it was used in the study made by Qaim and De Janvry (2005).

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

$$Log(VS) = Log(A) + \sum \beta_i Log(x) + \sum \beta_i (P) + Log(g(Z)) + \varepsilon \quad (5)$$

The parameter μ is interpreted as the fixed damage effect. A standard Cobb-Douglas production function treating pesticide and biological control as conventional production factors is also estimated for comparison purposes.

A problem in estimating production functions is that pest variables tend to be correlated with the production function error term ε. This is because unobserved factors like climate conditions can result in both high input levels of insecticides and low yields (Huang *et al.*, 2002) and also because insecticides applied to high responses of pest pressure can become a problem (Widawsky and et al., 1998).To address this problem, a two-stage least square (2SLS) estimation is used and the pesticide variable is instrumented. The instrumental variable (IV) has to have the following characteristics: cov (IV, ε) =0 as it should not be correlated with the error term, and cov (IV, pest) $\neq$0 and highly correlated. For the IV we will use the amount of active ingredient. Furthermore, production functions and pesticide use function are tested for multicollinearity and corrected for heteroskedasticity, two other potential problems with cross-sectional data.

Stochastic production frontier

In addition, to the 2 previous Cobb-Douglas models, a Stochastic Production Frontier (SPF) is estimated. In contrast to a regular production function, SPF allows for inefficiency as it does not assume that all farmers are producing on the production possibilities frontier.

The SPF estimates a frontier function that can be interpreted as the technological constraint for each farming system. How far from the frontier the farm operation is located addresses the farm's performance or technical efficiency. Traditional regression approaches, such as ordinary least squares (OLS), can be used to estimate parameters of production, cost, and/or profit functions; however, the estimates only reflect the average farm performance.

The stochastic frontier model considers random shocks on the production process. Assume that cross sectional data for the quantities of N inputs used to produce a single output are available to I producers. A SPF model is written as

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

Where Y_i is the scalar output of producer i, i = 1, . . . , I, X_i is a vector of N inputs used by producer i, f (X_i; β) is the deterministic production frontier, β is a vector of technology parameters to be estimated, exp $\{v_i\}$ captures the effects of statistical noise, and TE_i is the output oriented technical efficiency of producer i. [f (X_i; β) · exp $\{v_i\}$] is the SPF. It consists of two parts: a deterministic component f (X_i; β) common to all producers and a producer-specific component exp $\{v_i\}$ which captures the effect of random shocks on each producer.

Now equation (6) can be rewritten as

$$TE_i = \frac{Y_i}{f(X_i;\beta).\exp\{v_i\}} \qquad (7)$$

Which defines technical efficiency as the ratio of observed output to the maximum feasible output in an environment characterized by exp $\{v_i\}$. It follows that Y_i achieves its maximum feasible value of [f (X_i; β) · exp $\{v_i\}$] if and only if TE_i = 1. Otherwise TE_i < 1 provides a measure of the shortfall of observed output from maximum feasible output in an environment characterized by exp $\{v_i\}$, which is allowed to vary across producers. Rewrite equation (7) as

$$Y_i = f(X_i;\ \beta) \exp\{v_i\} \exp\{-u_i\} \tag{8}$$

Where TE_i = exp $\{-u_i\}$. This form is chosen due to the simplification when taking natural logarithms. Because we require that $TE_i \leq 1$, we have $u_i \geq 0$. Next, assume that f (X_i; β) is of the log-linear Cobb- Douglas form. Alternative functional specifications are conceivable but this specification is computationally convenient. The SPF model (8) becomes

$$\text{Log } Y_i = \beta 0 + \sum \beta_n \text{ Log } X_{ni} + v_i - u_i \tag{9}$$

Where v_i is the two sided individual "noise" component, and u_i is the nonnegative technical inefficiency component of the error term. The distributional assumptions are (i) v_i ~ i.i.d. N (0, σ_v^2); (ii) u_i ~ i.i.d. N+ (0, σ_u^2), that is, as nonnegative half normal; and (iii) v_i and u_i are distributed independently of each other and of the exogenous variables (Kumbhakar and Lovell, 2000). However, this Normal - Half Normal model implicitly assumes that the "likelihood" of inefficient behavior monotonically decreases for increasing levels of inefficiency. In order to generalize the model, allows u to follow a truncated normal distribution: (ii)' u_i ~ i.i.d. N+ (μ , σ_u^2), where μ is the mode of the normal distribution and is truncated below at zero. The Normal‐Truncated Normal model, which has the three distributional assumptions (i), (ii)', and (iii), provides a somewhat more flexible representation of the pattern of efficiency in the data (Kumbhakar and Lovell, 2000; Coelli *et al.*, 2005).

The density function of v is

$$f(v) = \frac{1}{\sqrt{2\pi\sigma_v}} \, . \exp\{-\frac{v^2}{2\sigma_v^2}\} \quad (10)$$

The truncated normal density function for u ≥ 0 is given by

$$f(v) = \frac{1}{\sqrt{2\pi\sigma_v\phi(^{\mu}/\sigma_\mu}} \, . \exp\{-\frac{(u-\mu)^2}{2\sigma_u^2}\} \quad (11)$$

Where Φ (·) is the standard normal cumulative distribution function. When μ = 0, the density function in equation (6) collapses to the half normal density function for the Normal-Half Normal model. Point estimates for technical efficiency of each producer can be obtained by means of

$$TE_i = \mathrm{E}\,[\exp\{-u_i\}\,|\varepsilon_i\,] \quad (12)$$

Where $\varepsilon_i = v_i - u_i$.

Results and discussion

Pesticide use function

Patterns of pesticide use with and without MI are shown in column (a) and column (b) respectively in Table 1. Heterogeneity was found to be characteristic of the sample but because of the limited amount of observations, the sample was not subdivided.

[Place Table 1 Approximately Here]

Unexpectedly, and in contrast of with what was found previously regarding biological control by Qaim and De Janvry (2003), the amount of pesticide used in plots also using MI is greater than in those who are not using it. A comparison between columns (a) and (b) shows that there is a 20% increase in pesticide use associated with MI use but is only 14% if we refer to pesticide active ingredient. However, this positive relationship could be explained by looking at some of the other variables as pest pressure and value of sales are 38% and 65% greater respectively on the plots using MI. It can be inferred then that farmers using MI have a bigger income and also bigger pest problems and use more pest products (biological or not). So, there is a mixed effect of costs increments (through the pesticide increase) and productivity gains.

The pesticide use function is estimated by an OLS Regression. Multicollineality detection was performed through a Variance Inflation Factor (VIF), being the average of 1.48 and never larger than 2.5 so it was not an issue. Robust standard errors were used to address heteroskedasticity concerns.

[Place Table 2 Approximately Here]

All coefficients of the insecticide use function (pest) show the expected signs. As it was showed in the summary statistics, MI, which in theory is supposed to be a substitute for pesticide, have a positive coefficient but is not significant. This positive coefficient goes against previous studies made in other crops like Cabbage (Jankowski *et al.*, 2007) and cotton (Qaim and de Janvry, 2005; Huang *et al.*, 2002). Nevertheless, the study made by Pemsl (2005) in cotton in china also had a positive coefficient, but as in our study, it was not significant. This results can fit some paradigms established about biocontrol like “the more a grower is willing to gamble the better prospect he is to accept the idea of biological control. Those growers who cannot afford to lose much (monetarily) usually do not want to risk using BC. They rather pay the price of "prevention" insecticide treatments than take a chance on BC not coming through for them. The prevention treatments are basically an insurance policy” (Peshin and Dhawan, 2009). Going back to the results, for 1 extra year of experience, farmers use 0.31% less pesticide. The price elasticity of pesticide use is -0.45%, i.e., if the pesticide price increases, by 1%, the amount of pesticide used is reduced by 0.45%, which likely confirms our “insurance” argument. The elasticity of pesticide use with respect to yield is 0.07 (for a 1% increase in yields, pesticide used is increased by 0.07%) suggesting that pesticides only marginally increase yields and perhaps mostly in the lower range. In the direct input category, for a 1% increase in trees, labor, bees, fertilizer and fuel, the pesticide use increases by 0.0082%, 0.032%, 0.011%, 0.0054%, and 0.09% respectively. This could be due to higher general production intensity or more indirectly as higher production inputs lead to higher yields and hence trigger higher insecticide use.

An interesting finding is that pesticide use increases with planted acres (production volume). Only the states of California and New York are significantly compared to Washington (the base). Pest pressure is a vector describing the degree of pest pressure exante (before spraying decisions). In this study it was found to be positive significant (as usually is expected), meaning that as pressure becomes worst there is an increase in pesticide use.

Production functions and frontier

As it can be seen in table 1, MI is positively correlated with the quantity of pesticides used, but also increases yields to a significant extent. The net yield effect can be estimated econometrically by using a production function approach. The first column in Table3 shows the results for the production function considering all inputs as equal. As it was explained before, multicollinearity and heteroskedasticity issues were tested and corrected. In addition, a Chow test was performed in order to see if the two groups of farmers could be pooled together. Also, the problem of endogeneity was addressed through a two stages least squares (2SLS) regression.

[Place Table 3 Approximately Here]

Microbial inoculatnts have a positive effect on output at the 10 % confidence level. All other parameters remaining equal (*ceteris paribus*), MI increases apples yields by 21.25% per hectare, which keeps up with what was speculated previously looking at the summary statistics. This also corroborates the results found by Qaim and De Janvry (2003) where they found that the use of Bt cotton increases yields by 507 kg./ha. in Argentina.

Insecticides also contribute substantially to higher yields. For a 1% increase in the amount of pesticides used, the yield increased by 19%. Labor has a positive effect on apples output. For a 1 % increase in labor, the expected output increases by 0.05%. The impact of fertilizers is also positive, but not statistically significant. The positive and significant coefficient at the harvested acres suggests economies of size in the production of apples.

With respects to the area dummies, all the states have negative significant coefficients except for California and Oregon. This means that, compared to the state of Washington, they produce less.

The coefficients of the production function with integrated damage control are very similar to those in the standard production model but in this case our variable of interest is no significant. MI has a t-value of 1.41 which is close to the minimum value to be significant. This can be due to the fact that we chose a logistic damage control function. Without any pest control inputs, crop damage would have been around 74%. As it was stated in the theory, it can be seen that parameters of pesticide use was overestimated at 0.19 as compared to 0.002 An interesting fact is that with the fixed damage effect of 74% and the marginal amount of damage contained by the pesticide of only 0.002% the damage could be enormous, but because the MI is addressing 65% of this damage at a 14% of level of confidence the parameters are acceptable. Again, all these little margins of errors could be due the damage functional form. Comparing these results to Qaim and De Janvry (2003) found shows quite a few similarities. They found a fixed effect of

57%, but in this case the biological control component was significant only at a 10% level of confidence which correspond to our findings. In contrast, Pemsl (2006) and Jankowski et al. (2007) found biological control values to be very insignificant and negatively significant respectively, which confirms that some of these products are facing a different paradigm or are still in process of development.

Lastly, going through the production frontier, we have some results similar to the regular production function but with some minor changes. Our variable of interest remains significant and actually gains more statistical power. In fact, it has increased the impact on the output from 21% to 25% while the pesticide impact on production decreases by 0.04%. The labor impact decreases by 0.01%. As an innovation, irrigation amount is now significant, contributing to the yields by 0.02%. This is maybe due apples growing in states where there is less drought. Economies of size still remain but has decreased going from 0.12% to 0.08%. The same states as in the previous models remain significant and with a negative sign, confirming that the state of Washington is the best in apples production. The average efficiency rate is 37% suggesting that there is room for improvement. Although none of the states is completely efficient in apples production, Washington and California were the ones who obtained higher efficiency rates.

Conclusion

This article has empirically analyzed the effects of the Microbial Inoculants (MI) technology on pesticide use and productivity in apple production in the United States.

Using the ARMS survey data statistics, it was found that farmers using the technology tend to have bigger pesticide application rates. However, as the MI use was also correlated with higher yields and higher pest pressures, a pesticide use model was estimated. The results showed that the use of the MI technology does not affect the use of chemical pesticides.

Biocontrol agents are a new approach of an integrated pest management (IPM) practices. According to this study, only 36% of the US apple producers were using them in 2007. Results showed that for this case, there was no significant impact on pesticide use. However, it is expected that in the future due to the increasing concerns about pesticide residues and more strictly regulations the incorporation of MI as an integrated pest management (IPM) tool will increased (Fravel, 2005).

Moreover, using different types of production functions, it was shown that MI adopters benefit significantly from higher yields compared to those not using it. A logistic damage control function was integrated into one of these production functions resulting in the technology being very close to being significant; that is why some other specifications such as the exponential or Weibull are recommended.

Efficiency rates for all apple producers were found to be around 37%. The states with the highest rates of efficiency were California and Washington.

The MI technology is an environmentally friendly alternative that can complement, rather than substitute, agricultural chemical use easing compliance with regulations and positively impacts yields. Even though the pesticide usage is not significantly impacted by the MI use, the overall on farmer’s income depends on the tradeoff between the amount expended on biological control and the extra income from the increase in yields. This will be researched in the near future.

Table1. Summary statistics of apples farmers

	(a) Using MI		(b) No using MI		(c) All plots	
Variable	mean	St. dev	mean	St. dev	mean	St. dev
Pest pressure	15.37	5.3672	11.08	8.73	12.19	8.22
Insecticide (lbs/acre)	73.64	59.99	61.21	46.43	65.33	51.52
Active ingredient (lbs/acre)	51.38	35.13	44.16	35.97	46.57	35.88
Value of sales ($/acre)	3136.13	3882.16	1894.207	5406.04	2504.84	6258.47
number of observations	197		344		541	

Table2. Pesticide use function

	coefficients		t value
experience	-0.0031	*	-1.83
price	-0.4478	***	-16.59
value of sales	0.0706	***	3.82
trees	0.0082	**	2.42
labor	0.0324	***	5.29
irrigation	0.0094		1.36
bees	0.0114	***	3.01
fertilizer	0.0054	**	2.06
fuel	0.0854	***	5.01
MI (dummy)	0.0801		1.46
acres harvested	0.2516	***	11.95
Michigan	-0.0965		-1.06
Oregon	0.1265		1.31
New York	-0.2654	***	-2.75
Pennsylvania	0.0079		0.07
North Carolina	0.0331		0.27
California	-0.9452	***	-6.34
Pest. pressure	0.0074	*	1.7
constant	10.9277	***	3.21
number of obs.	541		
R2 adjusted	0.56		

Note: Robust standard errors, *** p<0.01, ** p<0.05, * p<0.1

Table3. Production functions and stochastic production frontier

	(a)			(b)			(c)		
	Cobb-Douglas			logistic damage control			Cobb-Douglas frontier		
	coefficient		t value	coefficient		t value	coefficient		t value
active ingredient	0.1922	***	3.07				0.1519	***	3.49
experience	0.0016		0.34	0.0014		0.37	-0.0019		-0.59
trees	0.0001		0.02	0.0001		0.03	-0.0042		-0.68
labor	0.0487	***	2.83	0.0464	***	3.12	0.0368	***	3.13
irrigation	0.0027		0.18	0.0038		0.24	0.0229	*	1.84
bees	0.0117		1.32	0.0125		1.46	0.0053		0.74
fertilizer	0.0034		0.57	0.0032		0.54	0.0053		1.07
fuel	0.0319		0.77	0.0282		0.7	0.0281		0.93
MI (dummy)	0.2125	*	1.76				0.2475	**	2.45
Acres harvested	0.1226	**	2.52	0.1197	***	2.64	0.0846	**	2.32
Michigan	-0.7714	***	-4.36	-0.7414	***	-4.03	-0.7307	***	-4.89
Oregon	0.3297		1.62	0.3031		1.38	0.2783		1.52
New York	-0.4674	**	-2.51	-0.4296	**	-2.04	-0.4539	***	-2.61
Pennsylvania	-1.0899	***	-4.55	-1.0593	***	-5.05	-0.7996	***	-4.48
North Carolina	-1.6653	***	-6.01	-1.6812	***	-6.68	-1.2252	***	-5.54
California	0.3175		0.82	0.2272		0.64	0.4832		1.55
constant	2.221		0.23	3.8377		0.49	10.9868	*	1.64
Damage control fun.									
μ				0.7448	***	2.06			
active ingredient				0.0002	**	1.99			
MI (dummy)				0.6579	[a]	1.41			
number of obs.	547			547			547		
R2 adjusted	0.39			0.38			-		
average efficiency							0.37		

[a] significant at a 14% level

Note: Robust standard errors, *** p<0.01, ** p<0.05, * p<0.1

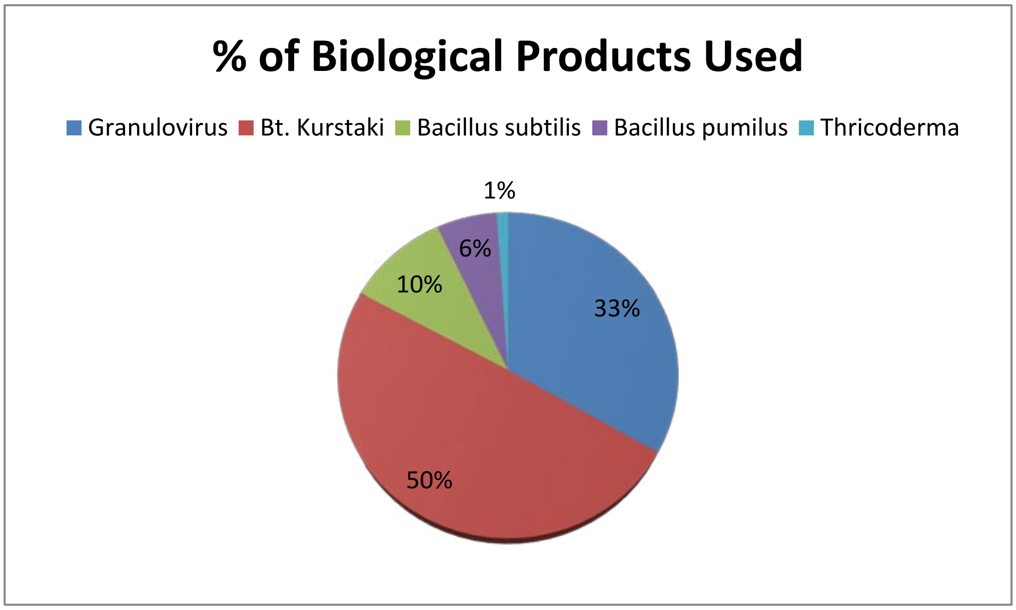

Figure 1. Market share of biocontrol agents for 2007 apples production

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