The Economic Impact of Corn Rootworm Resistant Maize in Minnesota from 2003-2012

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Abstract

An ex-post cost/benefit analysis of corn rootworm traits in the Minnesota corn seed market is performed using data from the introduction of corn rootworm traits in 2003 through 2012. Yield impacts, price premiums, and additional cost effects such as insecticide spending, crop insurance discounts, environmental impacts, and convenience factors are quantified and analyzed. Multiple linear regression models are created for yield and pricing over this time period, and products containing single and multiple corn rootworm traits are differentiated in the models. The results are used to estimate the realized cumulative financial impact, from the corn grower's perspective, of corn rootworm traits in Minnesota during this time frame.

Table of Contents

List of Tables

Introduction

The use of genetic modification (GM) in agriculture has seen a rapid increase throughout the world over the last two decades. Adoption of GM varieties has been most prominent in North and South America, and particularly in soybean and corn. Recent studies (Brookes & Barfoot 2012, James 2010, Fernandez-Cornejo et. al. 2014) generally report that positive economic benefits result from the adoption of biotech varieties over conventional (non-GM) crops. These economic advantages primarily derive from reduced chemical use and the additional yields of GM plants. Many of the empirical studies that have been performed previously focus on the impact of GM traits in corn that cause plant expression of the *Bacillus thuringiensis* (Bt) toxin to control above-ground pests, mainly lepidopteron pests and other corn borers (denoted throughout as ECB Bt).

This paper aims to quantify the economic benefits of corn hybrids containing a GM trait specifically targeting below-ground pests, namely corn rootworm (CRW) species over those hybrids that do not contain a CRW resistance trait, as well as differentiating between those hybrids that contain only one mode-of-action (MOA) for CRW control and those containing two MOAs. More specifically, it examines whether there is a statistically significant yield advantage for single MOA CRW hybrids, or dual MOA CRW hybrids, over non-CRW hybrids, and quantifies price premiums associated with one or two CRW traits, along with pesticide cost savings, and other relevant financial implications. The benefits and costs are then aggregated to draw conclusions on how the use of this technology could affect the profit of corn production farms in Minnesota compared to those farms that do not plant hybrids containing CRW traits.

The goals of the study were accomplished by analyzing yield, price, and non-pecuniary benefits. Yield trial data were provided by the University of Minnesota Agricultural Experiment Station (MAES). Hybrid pricing data were obtained from an annual nationwide farmer survey conducted by GfK Kynetec (GfK). Non-pecuniary benefits were compiled from other studies. This study is unique from previous publications in that it focuses on the CRW traits specifically, differentiates between single and multiple modes-of-action for CRW, uses experimental field data, uses proprietary hybrid pricing data, and also incorporates financial estimates of non-pecuniary benefits.

Analytical Framework

The objective of this paper can be accomplished using partial budgeting analysis. Partial budget analysis is a commonly used technique that allows farmers to evaluate potential budget impacts prior to making a decision. In partial budget analysis, only those portions of the budget that might be affected by a particular change are included in the calculations, and all other parts of the budget are assumed to be unchanged. In this paper, the key portions of the farm budget affected by CRW corn are assumed to be revenue (as a result of increased yield) and cost (reduced costs for less pesticide application, increased seed costs, reduced cost for crop insurance, and reduced costs for other non-pecuniary items). This results in a net change in profit for the farmer.

To compute the per acre extra profit of a variety containing CRW traits over the non-CRW technology, $\Delta\pi_{CRW}$, the model subtracts the total cost difference from using corn containing CRW traits versus corn that does not contain CRW traits, ΔC_{CRW}, from the additional revenue ΔR_{CRW} that the farmer obtains due to higher yields from the CRW traits:

$$\Delta\pi_{CRW} = \Delta R_{CRW} - \Delta C_{CRW}.$$

For the calculation of the total incremental cost of the CRW technology for CRW traits, the model takes into account only the variable costs that differ between the CRW trait technology C_{CRW}, and the non-CRW technology C_{non}:

$$\Delta C_{CRW} = C_{CRW} – C_{non}.$$

This formula was applied to each individual variable cost component, differentiating between single and dual CRW trait products when data is available, resulting in the incremental seed cost ΔC_S; pest management cost savings ΔC_{CP}; reduction in crop insurance premiums ΔC_I; and non-pecuniary impacts such as reduction of risk, convenience, environmental benefits, and worker safety ΔC_{NP}. The analysis assumes that all other costs not included in the calculation, whether fixed or variable, are consistent between the populations. Summing then yields

$$\Delta C_{CRW} = \Delta C_S + \Delta C_{CP} + \Delta C_I + \Delta C_{NP}.$$

The additional revenue as a result of the increased yield from CRW traits ΔR_{CRW} is found by taking the average per-acre revenue of the non-CRW corn, R_{non}, from the average per-acre revenue of the corn containing CRW traits, R_{CRW}:

$$\Delta R_{CRW} = R_{CRW} – R_{non}.$$

R_{CRW} and R_{non} are calculated by multiplying the average per acre yield of the CRW corn, Y_{CRW}, and the non-CRW corn, Y_{non}, with the commodity price, P, of corn per bushel (which does not vary between CRW corn and non-CRW corn[1]):

$R_{\mathbf{CRW}} = Y_{\mathbf{CRW}} * P$ and

$R_{\mathbf{non}} = Y_{\mathbf{non}} * P$.

Combining these formulas yields:

$\Delta R_{CRW} = (Y_{CRW} - Y_{non}) * P$ or $\Delta R_{CRW} = \Delta Y_{CRW} * P$.

To derive the yield advantage of CRW corn, ΔY_{CRW}, the benefit in yield associated with reduced refuge, ΔY_{Refuge}, is summed with the realized benefit in yield associated with the inclusion of a CRW trait, ΔY_{Trial}:

$\Delta Y_{CRW} = \Delta Y_{Trial} + \Delta Y_{Refuge.}$

The average per acre $\Delta\pi_{CRW}$ is calculated annually within the study period, and then multiplied by the corn acres in Minnesota planted each year, to determine an annual and cumulative estimate of the profit impact of CRW varieties from a grower perspective.

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[1] This analysis does not take into account any price premium that may be associated with organic corn, which would be a subsector of the non-CRW and non-GM corn market.

Empirical Methods

Implementation of this partial budget model requires information on:

1. Yield advantage or disadvantage (increased or decreased bushels per acre of hybrids containing one or two CRW traits compared to hybrids not containing a CRW trait), denoted throughout as ΔY_{Trial};
2. Price of the technology (incremental seed cost for hybrids containing one or two CRW traits compared to those not containing a CRW trait), ΔC_S;
3. Pest management (less chemical use for CRW corn), ΔC_{CP};
4. Ability to decrease required refuge acreage by inclusion of dual MOA CRW traits, ΔY_{Refuge};
5. Crop insurance premiums (lower insurance for CRW hybrids) ΔC_I;
6. Other non-pecuniary factors, including reduction of yield risk, operator and worker safety, environmental safety, and convenience, for which monetary estimates of value were obtained from previously published market research and farmer surveys, ΔC_{NP}; and
7. Commodity price of corn, P.

The data sources used in the study are from the MAES corn trials, from which ΔY_{Trial} was estimated; the GfK annual farmer surveys, from which ΔC_S was estimated; existing literature, from which estimates for ΔC_{CP}, ΔY_{Refuge}, ΔC_I, and

ΔC_{NP} were obtained; and the Chicago Board of Trade (CBOT) commodity pricing, from which annual estimates of P were obtained.

Yields Differences

The data used to calculate ΔY_{Trial} came from the MAES dataset. MAES is an organization affiliated with the University of Minnesota College of Food, Agricultural, and Natural Resource Sciences. The MAES performs variety trials of selected crops each year, including grain and silage corn, and publishes the results to be primarily used for variety comparison for commercial farming. The MAES dataset reflected corn hybrid trial plantings from 2003 to 2012. Multiple linear regression analysis was performed on the data, and the dependent variable identified for purposes of this study was corn hybrid yield, Y_{Trial}. Independent variables included:

1. Presence or absence of a single CRW trait (binary variable), denoted in the regression equation as x_1;
2. Presence or absence of dual CRW traits (binary variable), x_2;
3. Maturity group (numerical data between 88 and 105 days), x_3;
4. Presence or absence of a ECB Bt trait for corn borer/broad lepidopteran resistance (binary variable), x_4;
5. Location (fixed effect variable for each of the eleven trial locations, with one removed to avoid perfect collinearity), x_5, x_6, x_7, x_8, x_9, x_{10}, x_{11}, x_{12}, x_{13}, x_{14};

6. Previous crop planted on that piece of land (corn, soybeans, wheat, or dark red kidney beans), x_{15}; and
7. Planting date, x_{16}.

Therefore, the multiple linear regression equation is:

$$Y_{Trial} = \beta_0 + \beta_1 x_1 + \beta_2 x_2 + \beta_3 x_3 + \beta_4 x_4 + \beta_5 x_5 + \beta_6 x_6 + \beta_7 x_7 + \beta_8 x_8 + \beta_9 x_9 + \beta_{10} x_{10} + \beta_{11} x_{11} + \beta_{12} x_{12} + \beta_{13} x_{13} + \beta_{14} x_{14} + \beta_{15} x_{15} + \beta_{16} x_{16} + \epsilon$$

or

$$Y_{Trial} = \beta_0 + \sum_{i=1}^{16} \beta_i x_i + \epsilon$$

The hypothesis of the study is that the coefficients of the CRW variables, β_1 and β_2, would be positive and statistically significant, indicating that the inclusion of one or more CRW traits increases corn yield. The values of β_1 and β_2 return ΔY_{Trial} for one and two CRW traits, respectively.

To perform the regression, the presence or absence of a single CRW trait was converted to a binary variable, with the presence of one CRW trait recorded as 1, and the presence of two CRW traits or the absence of a CRW trait recorded as 0.

The presence or absence of dual CRW traits was converted to a binary variable, with the presence of two CRW traits recorded as 1, and the presence of only one CRW trait or the absence of a CRW trait recorded as 0.

Maturity group was included because it is well known that longer duration varieties typically produces higher yield. It is expected that the coefficient, β_3, of the maturity group variable would be positive.

The ECB Bt variable was also converted to a binary value. The ECB Bt group was assigned to be 1, and the non-ECB Bt group was coded as 0. It would be expected that β_4 would be positive, indicating that the presence of an ECB Bt trait increases corn yield.

Fixed effects for each trial location were included to account for differences in trial protocol. Since the trial locations were managed by different agronomists, they included different chemical, fertilizer, and herbicide application practices. In addition, soil series at each location can influence corn yield. For each trial, a location variable was assigned—for example, each data point from the Lamberton location was assigned a value of 1 for the Lamberton variable, and a 0 for all other locations' variables. Each year, data for one location was excluded from the dataset to avoid perfect collinearity in the regression analysis. This location varied from year to year, as the planting locations changed over the study period. There was no need for a hypothesis regarding expected effects of each location variable, although it is worth noting that the resulting analysis is in comparison to the location excluded.

The previous crop was examined because it is broadly accepted by farmers that planting corn two crops in a row ("corn on corn") increases the infestation of CRW pests in a given field and decreases soil fertility. In order to be able to be used in multiple linear regression analysis, the Previous Crop variable was converted to binary values. Because of the previously mentioned effect of planting corn on corn, it seemed reasonable to split the dataset into Previous Crop Corn and Previous Crop Not Corn groups. Previous Crop Corn was assigned a value of 1, and Previous Crop Not Corn was assigned a value of 0. It is expected that the coefficient of the Previous Crop Corn variable, β_{15}, would be negative, that is, that the lack of crop rotation would decrease corn yield.

Planting date was converted to a numeric value by the following process. The day of planting was divided by the number of days in that given month, and then added to the month. For example, a planting date of April 25th was converted to 4.83 (4 + 25/30). It is expected that the coefficient of the Planting Date variable, β_{16}, would be negative, that is, that the later a crop is planted, the lower the corn yield.

Hybrid Price Differences

The data used to calculate ΔC_S in this analysis were provided by GfK, an independent company that performs annual computer-assisted telephone surveys of farmers across the United States. The interviews collect detailed sample data on the acreage of seed planted, technology contained within the hybrids, and price paid for the corn seed. About 40-50% of those farms surveyed each year remain in the sample the following year (Shi, et al; 2010). This data is commonly used to evaluate trends across the corn seed industry such as the market share of each seed company, the prevalence of GM traits across the market, the approximate price of GM products and stacks, and the refuge requirements for each product.

This dataset reflects nationwide corn hybrid prices of all products sold by major seed companies from 2003 to 2012. Multiple linear regression analysis was performed on the data, using average price per bag of hybrid corn seed, C_S, as the dependent variable.

The independent variables included:

1. Presence or absence of a single CRW trait (binary variable), denoted in the regression equation as z_1;
2. Presence or absence of two or more CRW traits (binary variable), z_2;

3. Presence or absence of a single ECB Bt trait for resistance to corn borer or broad lepidopteran insects (binary variable), z_3;
4. Presence or absence of two or more ECB Bt traits for resistance to corn borer or broad lepidopteran insects (binary variable), z_4;
5. Presence or absence of a herbicide tolerance trait (binary variable), z_5;
6. Required refuge percentage (ranging from 5 to 20%), z_6; and
7. Presence or absence of refuge-in-bag (RIB) technology (binary variable), z_7.

Therefore, the multiple linear regression equation is:

$$C_S = \beta_0 + \beta_1 z_1 + \beta_2 z_2 + \beta_3 z_3 + \beta_4 z_4 + \beta_5 z_5 + \beta_6 z_6 + \beta_7 z_7 + \epsilon$$

or

$$C_S = \beta_0 + \sum_{i=1}^{7} \beta_i z_i + \epsilon$$

A binary variable for a single CRW trait, z_1, was included, assigning 1 to the presence of one such trait, and 0 otherwise. Note that a trait stack with 2 traits that control CRW pests was assigned a 0 to this variable. It is expected that the value of β_1 would be positive and statistically significant (i.e., that one CRW trait increases the seed cost).

A separate binary variable for two or more CRW traits, z_2, was also included. The presence of two or more such traits was assigned a 1, and 0 was assigned otherwise. Note that a product with zero or one such trait to control these pests was assigned a 0. It is expected that the value of β_2 would be positive and statistically significant (i.e., that two or more CRW traits increase the seed cost).

A binary variable for a single ECB Bt trait, z_3, was included, assigning 1 to the presence of one such trait, and 0 otherwise. Note that a trait stack with 2 or more ECB Bt traits was assigned a 0 to this variable. It is expected that the value of β_3 would be positive; that one ECB Bt trait increases the seed cost.

A binary variable for two or more ECB Bt traits, z_4, was also included. The presence of two or more such traits was assigned a 1, and 0 was assigned otherwise. Note that a product with zero or one ECB Bt traits was assigned a 0. It is expected that the value of β_4 would be positive; that two or more ECB Bt traits increase the seed cost.

The herbicide tolerance (HT) binary variable, z_5, was included to account for any price premium associated with herbicide tolerance. An overwhelming percentage (more than 85%) of trait stacks in the dataset contained tolerance to at least one herbicide. Presence of at least one HT trait was indicated by 1, lack of an HT trait was indicated by 0. It is expected that the value of β_5 would be positive; that HT traits increase the seed cost.

A variable for the required refuge percentage, z_6, was included, since the ability to reduce the amount of refuge required to be planted in a field can significantly impact overall yield. Among ECB Bt or CRW varieties, the refuge requirement ranged from 0.05 (5% refuge requirement – the lowest currently permitted in the industry) to 0.20 (20% refuge requirement – standard everywhere in the country except the cotton-growing areas of the Southern U.S.). It is expected that the value of β_6 would be negative; that as refuge percentage decreases, the seed cost increases.

A binary variable for the presence or absence of RIB technology, z_7, was also included. This technology was introduced in 2011, when seed companies began blending a percentage of conventional or HT seed (the refuge component) with insect-resistant seed, in the seed bag. This eliminates the requirement for farmers to plant and maintain a separate refuge area, while ensuring compliance with required refuge acreage. It is expected that the value of β_7 would be positive; that RIB increases seed cost.

Results

First, this section details the results of the multiple regression analysis that was performed with both the yield and pricing data to test the null hypothesis that all of the variables' regression coefficients are equal to 0. Specifically, for the yield regression equation, this study is most interested in the results from the null hypothesis that β_1 and β_2 (coefficients of the CRW yield variables) are equal to 0, and for the pricing regression equation, this study is most interested in the null hypothesis that β_1 and β_2 (coefficients of the CRW pricing variables) are equal to 0. Second, these regression results are used to guide the partial budget analysis for CRW corn.

Yield Analysis

The yield analysis was conducted annually on the MAES yield trial data, with yield (bu/acre) as the dependent variable. The results of this analysis including coefficient estimates, R^2 statistics, and observations are reported in Table 1. Variables with N/A were either not included in that year or were removed to eliminate perfect collinearity between variables. This includes the variable Planting Date, which was removed from the regression analysis in all years because of perfect collinearity with the planting locations.

Table 1: Coefficients and Statistical Significance Resulting from Analysis of Variance (ANOVA) for Multiple Linear Regression Analysis – Yield Data, 2003-2012

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
R-squared	0.84	0.80	0.63	0.78	0.65	0.70	0.75	0.64	0.60	0.75
Observations	735	931	836	1190	1296	1039	940	811	735	673
Intercept	122 ***	251 ***	81 ***	53 ***	35 ***	154 ***	242 ***	52 ***	101 ***	99 ***
Maturity	0.4 ***	-0.3 ***	1.4 ***	1.8 ***	1.0 ***	0.6 ***	-0.2	1.5 ***	0.7 ***	1.2 ***
Previous Crop Corn	62.0 ***	N/A	2.5	4.7 **	60.9 ***	-59.8 ***	-67.9 ***	-29.2 ***	-3.3	N/A
Single CRW	-3.8	-3.2	2.2	-1.9	5.1 ***	-0.8	0.4	-1.9	-1.2	-1.9
Dual CRW	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-1.1	0.9	-2.3
ECB Bt	5.4 ***	1.3	4.2 ***	2.4 **	3.8 ***	2.0	2.8	2.2	4.8 *	8.7 ***
Waseca	-27.8 ***	-17.7 ***	-6.9 ***	-9.5 ***	68.2 ***	-49.1 ***	N/A	-26.7 ***	40.6 ***	-15.8 ***
Rochester	N/A	N/A	N/A	N/A	37.5 ***	-18.5 ***	-38.7 ***	-17.5 ***	18.7 ***	35.4 ***
Lamberton	-6.9 ***	-16.8 ***	-38.4 ***	-6.7 ***	4.2 *	N/A	-30.0 ***	-15.9 ***	16.7 ***	-17.6 ***
Hutchinson	N/A	N/A	N/A	N/A	N/A	N/A	N/A	48.9 ***	44.2 ***	N/A
Morris	41.7 ***	-45.0 ***	0.2	-36.6 ***	40.3 ***	-22.6 ***	-72.9 ***	-25.8 ***	16.9 ***	N/A
Rosemount	-38.1 ***	-50.5 ***	-29.7 ***	-37.6 ***	N/A	-76.8 ***	-13.7 ***	-1.2	32.1 ***	-36.4 ***
Crookston	N/A	N/A	N/A	-54.1 ***	55.3 ***	-49.3 ***	-88.0 ***	17.1 ***	-26.0 ***	-57.1 ***
Staples	N/A	-91.5 ***	N/A	N/A	N/A	N/A	N/A	N/A	32.1 ***	30.4 ***
Fergus Falls	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-20.0 ***
Rothsay	21.3 ***	-88.8 ***	-42.1 ***	-52.2 ***	24.7 ***	-30.4 ***	-51.6 ***	N/A	N/A	N/A

Statistical significance:

*** Statistically significant at 99% level

** Statistically significant at 95% level

* Statistically significant at 90% level

R^2 values ranged between 60% in 2011 and 84% in 2003. Comparing these R-squared values to other published studies that used corn yield as the dependent variable and which have been able to predict, on the high end, between 51% and 94% of variation (Tannura, et al. 2008; K. Liu, et al. 2011; Cai, et al. 2012), reveal that this study's regression equation compares favorably against other published models.

In every year, the hypothesis was rejected that all of the regression coefficients were 0. Further, most of the parameter estimates were consistent with expectations in both magnitude and sign (+/-), with the exception of the CRW variables.

The single and dual CRW variables were found to be statistically insignificant in all years except 2007, when the single CRW variable was found to be significant and positive. The result from the majority of the years goes against the hypothesis that the inclusion of one or more CRW traits will increase yield. There are several possible explanations for this:

1. There could be multicollinearity occurring between the CRW variables and the ECB Bt variables, since many hybrids contain stacked traits. There is very low correlation between the CRW variables and the ECB Bt variables in the early years when stacks were less common, and CRW tended to be sold as a single or with HT traits. This correlation increased as stacks became more common; 2010 and 2011 had the highest correlation between these variables, at 0.45. This multicollinearity could be

contributing to the model showing no statistically significant yield increase from the CRW traits in most years.

2. Other studies have reported lowered yields for CRW hybrids compared to non-CRW hybrids, as a result of yield drag or event lag (Shi, et al. 2013).
3. Trial data has been reported to show lower yield benefits from GM insect traits than farmer survey data, because pest damage in non-GM crops is often more severe in farmers' fields than on well-managed experimental plots (Klumper, Qaim, 2014).

The Maturity variable, in most years, was found to have a consistently positive coefficient that was under 1.5. Assuming an average of 1.0 for this variable, this can roughly be interpreted as one additional bushel in yield for each additional day of maturity.

The variable Previous Crop Corn, which was a binary variable (1 indicating Previous Crop Corn, 0 indicating Previous Crop Not Corn) was a difficult variable to interpret. In many of the years, only a single location planted corn the previous season, so the location variable had to be removed to avoid perfect collinearity, and as such, the Previous Crop Corn variable is accounting for the variation in the location as well as the effects of planting corn-on-corn. Previous Crop Corn would be expected to have a negative coefficient, since soil nutritional deficiencies and sustained pest lifecycle can result from planting corn-on-corn.

In about half the years, Previous Crop Corn had a strong negative effect on yield. However, in the other years, this variable was found to be insignificant or positive. Planting corn-on-corn could have a reduced effect in small acreage trial data when nutritional deficiencies are potentially offset by fertilizers, when pests are controlled by insect traits, or when CRW pests are not present in a given field in a given year. This could suggest a possible interaction effect between the CRW variable and Previous Crop Corn variable.

The ECB Bt variable had a positive coefficient that was statistically significant in most years, as expected. It can be interpreted to mean that the presence of an ECB Bt trait in a corn hybrid was found to increase corn yield by up to 8.7 bu/a. The magnitude of this coefficient is perhaps slightly lower than expectations, considering that the findings of previous studies have estimated yield increases of up to 20-30 bu/ac as a result of using ECB Bt corn in heavy pest pressure areas (Benbrooke, 2001). Other studies have demonstrated yield benefits of approximately 5-7% (Brookes & Barfoot, 2012; Marra, et al., 2002; and James, 2002). However, the realized benefit of an ECB Bt trait is heavily dependent on the magnitude of European Corn Borer pressure in the area, which was not measured in the estimated model.

The location variables served as fixed-effects variables and, while helpful in serving as a tool to improve the annual fit of the models, do not return coefficients that are useful to discuss in this study. However, the location variables' coefficients were consistently found to be significant.

Price Analysis

Analysis of the GfK survey data was also run annually, with product price ($/bag of seed) as the dependent variable. Table 2 summarizes the regression coefficients, R^2 and observations.

The R^2 for these regressions varies from 26% in 2003 to 79% in 2011. The year with the lowest R^2 was also the year with the fewest data points. There were only 12 different trait products sold that year, whereas the other years had more diverse product offerings.

In every year, the hypothesis is rejected that all the regression coefficients were 0. Further, most of the parameter estimates were consistent with expectations in both magnitude and sign (+/-).

The Intercept coefficient could approximate the price of a conventional hybrid, and therefore could possibly represent the price per bag of seed deriving from the genetics, combined with other corn market demand impacts (such as commodity price of corn) that would affect seed pricing. This parameter is relatively stable for the first four years of the data, and then jumps sharply in each subsequent year, particularly between 2010 and 2011. These fluctuations can likely be explained by the corresponding steep increases in the commodity price of corn in those years.

Table 2: Coefficients and Statistical Significance Resulting from Analysis of Variance (ANOVA) for Multiple Linear Regression Analysis – Pricing Data, 2003-2012

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
R-squared	0.26	0.69	0.47	0.69	0.57	0.45	0.52	0.66	0.79	0.61
Observations	12	19	22	27	29	32	30	30	32	43
Intercept	91.2 ***	85.1 ***	91.1 ***	91.8 ***	97.8 ***	114.1 ***	119.4 ***	127.4 **	172.6 ***	188.3 ***
Herbicide tolerance	1.4	6.6	2.3	10.5 *	10.3 **	21.9 *	26.9 *	26.4 *	20.2 **	25.1 *
Single ECB Bt	6.9	17.7 ***	15.7 ***	16.3 ***	11.7 ***	3.1	19.0 *	26.4 **	11.3	3.7
Single CRW	32.7	36.4 ***	17.3 ***	26.4 ***	18.2 ***	34.7 ***	32.8 ***	32.5 ***	29.9 ***	37.8 ***
Dual ECB Bt	N/A	N/A	N/A	N/A	N/A	N/A	57.6 **	51.9 *	34.8 ***	21.5 *
Dual CRW	N/A	N/A	N/A	N/A	N/A	N/A	N/A	86.4 **	36.1 **	32.0 **
Required refuge	N/A	N/A	N/A	N/A	N/A	N/A	N/A	12.3	-107.0	-88.7
RIB	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	18.3	9.8

Statistical significance:

*** Statistically significant at 99% level

** Statistically significant at 95% level

* Statistically significant at 90% level

The coefficient for Herbicide Tolerance is significant and positive in most years, as expected. The resulting price premium per bag of seed for herbicide tolerance is found to be approximately $10-25 over the study period, and was relatively stable between 2008 and 2012.

The coefficients for Single CRW trait and Dual CRW trait were found to be positive and statistically significant in all years except the initial year of launch, 2003. This is as expected. The price premium ranged from about $17 to $38 per bag of seed for Single CRW traits, and from $32 to $86 per bag of seed for Dual CRW traits.

A single ECB Bt trait has a coefficient that was found to be positive and statistically significant in 60% of the study years. It was found to be statistically insignificant in the other four years. When significant, the price premium ranged from about $12 to $26 per bag of seed, and did not increase linearly over time, but rather fluctuated up and down.

The dual ECB Bt trait variable had a positive coefficient ranging from $21 to $58 per bag of seed, and this was significant in all years. The initial year of product launch had the highest price premium for this component, dropping each subsequent year.

The Required Refuge and RIB variables were found to be statistically insignificant in each year; that is, no price premium was found to be associated with these variables. It could be that since these new technologies are inherently linked to multiple trait stacks, the price premiums for these technologies were packaged into the realized price premiums for dual ECB Bt and dual CRW traits.

Partial Budget Analysis

Costs

ΔC_{CRW} was calculated annually for single and dual CRW traits. Table 3 summarizes the calculations.

Table 3: Calculation of Incremental Cost (**ΔC_{CRW}**) for Single and Dual Trait CRW Acres ($/acre), 2003-2012

Single Trait CRW Acres (n = 1)										
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ΔC_{S1} ($/ac)[2]	12.10	13.48	6.40	9.79	6.72	12.85	12.15	12.03	11.08	13.98
ΔC_{CP1} ($/ac)[3]	-4.06	-4.06	-4.06	-4.06	-4.06	-4.06	-4.06	-4.06	-4.06	-4.06
ΔC_{I1} ($/ac)[4]	N/A	N/A	N/A	N/A	N/A	-10.65	-10.65	-10.65	-10.65	-10.65
ΔC_{NP1} ($/ac)[5]	-1.01	-1.01	-1.01	-1.01	-1.01	-1.01	-1.01	-1.01	-1.01	-1.01
Sum total = ΔC_{CRW1} ($/ac)	7.03	8.41	1.33	4.72	1.65	-2.87	-3.57	-3.69	-4.64	-1.74
Dual Trait CRW Acres (n = 2)										
ΔC_{S2} ($/ac)[2]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	31.98	13.38	11.84
ΔC_{CP2} ($/ac)[3]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-4.06)	-4.06	-4.06
ΔC_{I2} ($/ac)[4]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-10.65	-10.65	-10.65
ΔC_{NP2} ($/ac)[6]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-8.50	-8.50	-8.50
Sum total = ΔC_{CRW2} ($/ac)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	8.77	-9.83	-11.37

[2] Planting rate of 2.7 acres/bag is used to convert the seed cost numbers from $/bag to $/acre.
[3] Expected savings from pest management cost from the inclusion of CRW trait in corn hybrids is approximately $4.06/acre in the Central region of the U.S. (Marra, et al., 2010).
[4] Through the Agricultural Risk Protection Act of 2000, starting in 2008 farmers electing to plant biotech varieties could receive discounts on crop insurance premiums averaging $10.65/acre (Marra, et al., 2012).
[5] Reduction in risk from single CRW hybrids was estimated at $0.80/acre (Alston, et al., 2002) and environmental benefits quantified at $0.21/acre (Marra, et al., 2012).
[6] Reduction in risk from dual CRW hybrids was estimated at $6.50/acre (Marra, et al., 2010) and environmental benefits quantified at $2.00/acre (Marra, et al., 2012).

Yields

ΔY_{CRW} was calculated annually for single and dual CRW traits. Table 4 summarizes the calculations.

Table 4: Calculation of Incremental Yield (**ΔY_{CRW}**) for Single and Dual Trait CRW Acres (bushels/acre), 2003-2012

Single Trait CRW Acres (n = 1)										
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ΔY_{Trial1} (bu/ac)[7]	0	0	0	0	5.0	0	0	0	0	0
$\Delta Y_{Refuge1}$ (bu/ac)[8]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A	N/A
Sum total = ΔY_{CRW1} (bu/ac)	0	0	0	0	5.0	0	0	0	0	0
Dual Trait CRW Acres (n = 2)										
ΔY_{Trial2} (bu/ac)[9]	0	0	0	0	0	0	0	0	0	0
$\Delta Y_{Refuge2}$ (bu/ac)[10]	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1.19	1.19	1.19
Sum total = ΔY_{CRW2} (bu/ac)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	1.19	1.19	1.19

[7] No statistically significant yield difference for years 2003-2006, 2008-2012 for single CRW hybrids.
[8] Reduced refuge not applicable for single CRW varieties.
[9] No statistically significant yield difference in any years for dual CRW hybrids.
[10] Reduced refuge attributed to dual CRW traits increases yield by 1.19 bu/ac (Marra, et al., 2012)

Revenues

ΔR_{CRW} was calculated annually for single and dual CRW traits. Table 5 summarizes the calculations.

Table 5: Calculation of Incremental Revenue (**ΔR_{CRW}**) Benefit of Single and Dual CRW Corn ($/acre), 2003-2012

Single Trait CRW Acres (n = 1)										
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ΔY_{CRW1} (bu/ac)	0	0	0	0	5.0	0	0	0	0	0
P ($/bu)[11]	2.27	2.47	1.96	2.28	3.39	4.78	3.75	3.83	6.01	6.67
Product total = ΔR_{CRW1} ($/ac)	0	0	0	0	16.95	0	0	0	0	0
Dual Trait CRW Acres (n = 2)										
ΔY_{CRW2} (bu/ac)	0	0	0	0	0	0	0	1.19	1.19	1.19
P ($/bu)	2.27	2.47	1.96	2.28	3.39	4.78	3.75	3.83	6.01	6.67
Product total = ΔR_{CRW2} ($/ac)	0	0	0	0	0	0	0	4.56	7.15	7.94

[11] Data source for commodity pricing is USDA NASS.

Profit

$\Delta\pi_{CRW}$ was calculated annually for single and dual CRW traits. Table 6 summarizes the calculations.

Table 6: Calculation of Incremental Profit (**$\Delta\pi_{CRW}$**) of Single and Dual CRW Corn ($/acre), 2003-2012

Single Trait CRW Acres (n = 1)										
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
ΔR_{CRW1} ($/ac)	0	0	0	0	16.95	0	0	0	0	0
ΔC_{CRW1} ($/ac)	7.03	8.41	1.33	4.72	1.65	-2.87	-3.57	-3.69	-4.64	-1.74
$\Delta\pi_{CRW1}$ ($/ac)	-7.03	-8.41	-1.33	-4.72	15.30	2.87	3.57	3.69	4.64	1.74
Dual Trait CRW Acres (n = 2)										
ΔR_{CRW2} ($/ac)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	4.56	7.15	7.94
ΔC_{CRW2} ($/ac)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	8.77	-9.83	-11.37
$\Delta\pi_{CRW2}$ ($/ac)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-4.21	16.98	19.31

Total profit impact was calculated annually for single and dual CRW corn acreage in Minnesota. Table 7 summarizes the calculations.

Table 7: Calculation of Profit Impact of Single and Dual CRW Traits in Minnesota ($m), 2003-2012

Single Trait CRW Acres (n = 1)										
	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012
$\Delta\pi_{CRW1}$ ($/ac)	-7.03	-8.41	-1.33	-4.72	15.30	2.87	3.57	3.69	4.64	1.74
MN Corn Acres (m)[12]	6.65	7.05	6.85	6.85	7.85	7.2	7.15	7.3	7.7	8.33
% single CRW [13]	0.30	2	4	11	25	41	49	51	49	45
Total Profit Impact ($m)	-0.14	-1.19	-0.36	-3.56	30.03	8.47	12.51	13.74	17.51	6.52
Dual Trait CRW Acres (n = 2)										
$\Delta\pi_{CRW2}$ ($/ac)	N/A	N/A	N/A	N/A	N/A	N/A	N/A	-4.21	16.98	19.31
MN Corn Acres (m)[12]	6.65	7.05	6.85	6.85	7.85	7.2	7.15	7.3	7.7	8.33
% dual CRW[14]	0	0	0	0	0	0	0	3	6	8
Total Profit Impact ($m)	0.00	0.00	0.00	0.00	0.00	0.00	0.00	-0.92	7.84	12.87

[12] Data source for annual MN corn acres is USDA NASS.
[13] Data source for annual percent of corn acres containing a single CRW trait is GfK grower surveys.
[14] Data source for annual percent of corn acres containing dual CRW traits is GfK grower surveys.

The total profit impacts of single and dual CRW traits in Minnesota were summed annually and cumulatively. Table 8 summarizes the calculations.

Table 8: Total Estimated Profit Impact of CRW Traits in Minnesota ($m), 2003-2012

	2003	2004	2005	2006	2007	2008	2009	2010	2011	2012	Total, 2003-2012
Profit Impact, Single CRW trait ($m)	-0.1	-1.2	-0.4	-3.6	30.0	8.5	12.5	13.7	17.5	6.5	83.5
Profit Impact, Dual CRW trait ($m)	0.0	0.0	0.0	0.0	0.0	0.0	0.0	-0.9	7.8	12.9	19.8
Total Profit Impact for CRW traits ($m)	-0.1	-1.2	-0.4	-3.6	30.0	8.5	12.5	12.8	25.4	19.4	103.3

According to these models and calculation methods, the introduction of CRW traits has impacted grower profit in Minnesota positively by approximately $103 million over the period 2003-2012. There was a negative impact during the first years of trait introduction, for both the single and the dual, and then a sharp increase in financial benefit to the grower in subsequent years. This will be further discussed in the next section.

Discussion

Using National Data in Calculations:

One limitation of the data sources used to estimate grower profit in this study is that they are not specific to Minnesota, but rather are from nationwide grower surveys or previous studies that are not Minnesota-based. This analysis has made the assumption that inputs into the profit equation that are based on non-Minnesota data are able to be applied directly to Minnesota acres, but that may not be the case. For example, when it comes to hybrid pricing, nationwide data may not be accurate. The prices of hybrids containing CRW traits will tend to be higher in areas of high CRW pressure, which includes much of Minnesota. This could result in the price premium being underestimated. However, since the highest volume of CRW products will be sold in areas of high CRW pressure, and this study used a weighted average price, the discrepancy between Minnesota pricing and weighted-average nationwide pricing is likely minimized.

The Effect of Growing Conditions on Yield:

Although this yield dataset did not show a significant yield advantage or disadvantage to the inclusion of one or two CRW traits, it has been reported in other publications that in years of difficult growing conditions, the presence of a

CRW trait minimizes yield loss that a farmer might otherwise experience. That is, if a corn plant is weakened by external factors such as non-favorable weather, the CRW pest might be able to more easily cause yield-impacting damage. Likewise, in ideal growing conditions, the plant might be strong enough to overcome slight damage from the CRW pest, making the benefits from a CRW trait less pronounced (Purdue University, Field Crops IPM; and Marra, et al., 2012). Corn hybrid trials, such as the MAES trials, might tend toward ideal growing conditions, since the trials are conducted on small acreage plots which could be more easily monitored for water, fertilizer, insecticide, fungicide, and herbicide needs. As mentioned earlier and consistent with previous studies, trial results may not be representative of large acre farm growing conditions (Klumper, Qaim, 2014).

In summary, other related research has found that CRW traits have the most beneficial impact during years of difficult growing conditions and overall lower yields. Since the growing conditions within a university trial might not replicate actual broad acreage growing conditions accurately, it would be beneficial to the overall profit analysis to include yield results from a long-term study of farmer-reported data comparing yield of CRW hybrids with non-CRW hybrids.

Impact of Price Premium on Grower Profit:

According to the models and calculation methods used above, there was a negative financial impact from the grower's perspective during the first years of CRW trait introduction, for both the single and the dual, and then a positive impact in subsequent years. It is worth noting that at product launch, the price premiums that the model estimated for these new technologies are at their highest at the years of launch, and then tended to drop over subsequent years. From this perspective, the price premium of new technologies seems to be effectively acting as the biggest driver of grower profit.

Incremental RIB Benefits:

One piece of information that was not included in this analysis, but that has been previously reported in other related studies as a quantifiable benefit of trait stacks, including CRW traits, is the incremental benefit of Refuge-In-Bag technology (RIB). Although the benefit of a lower required refuge was included in the calculations above, there is an additional reported benefit of approximately $18.30/acre from hybrids that have a 5% RIB over those hybrids that have a requirement of 5% structured refuge. The reason for excluding this in the above calculation of benefit is because the inclusion of one or more CRW traits is not viewed as a direct cause of this change. A hybrid that contains two CRW traits can be classified as either 5% structured refuge, or 5% RIB. So, while the additional benefit of $18.30/acre could not be realized without the inclusion of CRW traits, the CRW traits are not the driving factor. However, it is worth mentioning that as corn hybrids shift to RIB technology, there is an additional per acre benefit that the grower could realize.

<u>Additional Unquantified Variables:</u>

There are several unquantified factors that should be discussed as potential benefits and risks of using CRW technology. These have not been included in the numeric calculations of revenue, profit, and costs that were performed above, but should be mentioned in this paper in order to fully capture the potential impact of CRW traits.

According to several sources (Brookes & Barfoot, 2012; Phipps & Park, 2002; Marra et al., 2012), there are several secondary positive effects on the environment resulting from lowered pesticide use.

- Significant diesel savings and lowered carbon dioxide emissions being released into the atmosphere;
- A widespread reduction in target pests as a result of the majority of fields using GM crops can result in less insect damage and less insecticide use in conventional (non-GM) crops;

- Lowered incidence of insecticide poisonings in agricultural workers, particularly in developing countries;

In addition, there are unquantifiable potential downsides to using CRW traits. According to research done by the International Service for the Acquisition of Agri-Biotech Applications, risks to the environment include:

- Insect resistance to CRW traits, particularly if proper refuge requirements are not maintained (resistance to CRW trait MON88017 has been documented in recent years (Gassmann et al., 2011))[15];
- Impact on non-target organisms in the environment;
- Whether the modified crop might persist in the environment longer than usual or invade new habitats; and
- Likelihood and consequences of “out-crossing,” where a gene is transferred unintentionally from the GM crop to another species.

While this analysis has not attempted to quantify these potential benefits and risks and has therefore excluded them in the cost/benefit analysis performed above, they should be included in the overall “big picture” evaluation of CRW traits. Further study of these potential benefits and risks are recommended in subsequent analyses.

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[15] While the inclusion of a second CRW trait can provide benefits from an insect resistance management perspective, this has not been included as a factor in this study.

Conclusions

This analysis has found that between 2003 and 2012, a typical grower in Minnesota likely did realize incremental profit from the utilization of single or dual CRW traits. However, nearly the entire benefit came in the form of reduced costs and reduced risks. This study's trial data showed that additional yield was not achieved through the use of CRW corn versus non-CRW corn in most years. Yet there was a price premium assessed for CRW corn over these years, between about $17 and $38 per bag for single CRW traits, and between about $32 and $86 per bag for dual CRW traits. Including this price premium and accounting for the reduction in various costs and risks, the per acre profit impact on a grower in Minnesota over this period ranged from about -$8 to +$19 per acre, depending on year and technology used. The technology costs were found to be greatest in the initial year of technology introduction, and for this reason, growers should carefully consider the increased costs when determining whether or not to adopt new technology in the first year of launch.

By extrapolating this per acre benefit across relevant Minnesota corn acreage, there was a total estimated positive benefit to Minnesota growers as a result of CRW technology of approximately $103 million from 2003 to 2012.

Recommendations

There are several main challenges encountered in creating these models and subsequent profit estimation, and a future study could adjust for these to obtain more accurate results. These challenges include:

1. As previously mentioned, the pricing dataset and several of the cost inputs came from data sources that are not specific to Minnesota.
2. Annual data were not always available for each variable input in the Profit equation, so in some cases, constants were used.
3. There was not always data available for each variable input to differentiate between single and dual CRW traits.
4. There could be multicollinearity between the ECB Bt variables and the CRW variables since many of the hybrids in the dataset contain trait stacks, and the individual traits' contributions to the yield are difficult to isolate.

The first of these challenges, using data that is not specific to Minnesota, recognizes that the pricing data used to create the price regression was generated from nationwide grower surveys. Using grower surveys is appropriate, but a future study could be improved by filtering the survey results to include only respondents from Minnesota. In addition, it would be helpful to use data for the additional technology cost variables (cost of crop protection, crop insurance, and non-pecuniary costs) that are specific to Minnesota acreage as well. When calculating the total profit, this study used U.S. data for the percentage of hybrids containing single or dual CRW traits. This likely underestimates the actual use of CRW traits in Minnesota, since CRW is not a major concern for growers in the southern U.S. To improve accuracy, a future study should use Minnesota-specific percentages to approximate the use of CRW traits.

The second challenge regarding annual data availability refers to the fact that for a few variables in the profit equation, such as pesticide savings and crop insurance discounts, these costs were assumed to be static over the years. This is likely incorrect, as inflation, new insecticide product launches, pricing fluctuations, annual incentive discounts, and other factors would likely cause the price of these variables to change over the years. To improve accuracy of calculations, a future study could quantify these variables on an annual basis.

The third challenge, lack of differentiating data for single and dual CRW trait stacks, builds on the second challenge. For some of the same cost variables that were assumed to be constant over the study period, data were not available to differentiate between products containing one or two CRW traits. For example, pesticide savings was likely underestimated for dual CRW trait stacks, since adding a 2nd MOA could allow growers to further reduce their pesticide use in the short term, as well as preventing insect resistance and additional pesticide use in the long-term. Obtaining estimates of these values for single and dual CRW products would further improve the accuracy of the calculations.

The fourth challenge, potential multicollinearity between ECB Bt traits and CRW traits, could be corrected by including in the dataset a large sample of hybrids that contain only ECB Bt traits and other hybrids that contain only CRW traits. Hybrids containing both types in a stack could also be included in the dataset, but there would need to be enough of the differentiating hybrids to lower the correlation between the ECB Bt variables and the CRW variables to an insignificant level.

Bibliography

Alston, J.M., Hyde, J., Marra, M.C., & Mitchell, P.D. (2002). An ex ante analysis of the benefits from the adoption of corn rootworm resistant transgenic corn technology. AgBioForum, 5(3), 71-84. Available on the World Wide Web: http://www.agbioforum.org/v5n3/v5n3a01-alston.htm.

Benbrook, Charles M (2001). The Farm-Level Economic Impacts of Bt Corn from 1996 through 2001: An Independent National Assessment. Available on the World Wide Web: http://www.biotech-info.net/Bt_corn_FF_final.pdf

Bledsoe, Larry W. and Obermeyer, John L (2010). Managing Corn Rootworms. Purdue Extension E-49-W. Available on the World Wide Web: http://extension.entm.purdue.edu/publications/E-49.pdf

Brookes, Graham & Barfoot, Peter (2012). GM crops: global socio-economic and environmental impacts 1996-2010. PG Economics Ltd, UK.

Cai, Ruohong, Yu, Danlin, & Oppenheimer, Michael (2012). “Estimating the Effects of Weather Variations on Corn Yields using Geographically Weighted Panel Regression.” Selected Paper prepared for presentation at the Agricultural & Applied Economics Association’s 2012 AAEA Annual Meeting, Seattle, Washington. Available on the World Wide Web:

http://ageconsearch.umn.edu/bitstream/124627/2/Estimating%20the%20Effects%20of%20Weather%20Variations%20on%20Corn%20Yields%20using%20Geographically%20Weighted%20Panel%20Regression.pdf

DiFonzo, Chris & Cullen, Eileen (2012). Handy Bt Trait Table. Available on the World Wide Web:

http://corn.agronomy.wisc.edu/Management/pdfs/Handy_Bt_Trait_Table.pdf

Gassman, A.J., Petzold-Maxwell, J.L., Keweshan, R.S., & Dunbar, M.W. (2011). Field-evolved resistance to Bt maize by western corn rootworm. PLoS ONE, 6(7).

GfK Kynetec. (2003-2012). TraitTrak data [Data file]. Retrieved from www.gfk.com.

Gómez-Barbero, M., Berbel, J., & Rodríguez-Cerezo (2008). E. Bt corn in Spain - the performance of the EU's first GM crop. Nature Biotechnology 26, 384-386. doi:10.1038/nbt0408-384

Hicks, D.R. (2006). Planting Dates and Minnesota State Average Corn Yields, 1968-2005; Available on the World Wide Web:

http://www.extension.umn.edu/cropenews/2006/06MNCN08.htm

International Service for the Acquisition of Agri-Biotech Applications; Pocket K No. 4: GM Crops and the Environment. Available on the World Wide Web: http://www.isaaa.org/resources/publications/pocketk/4/

Klümper W, Qaim M (2014) A Meta-Analysis of the Impacts of Genetically Modified Crops. PLoS ONE 9(11): e111629. doi:10.1371/journal.pone.0111629

Kruppa, Bertalan (2011). The potential economic impact of the western corn rootworm resistant GM variety on maize production in Hungary. Available on the World Wide Web:http://ageconsearch.umn.edu/bitstream/104678/2/15_Kruppa_The%20potential_Apstract.pdf

Liu, K., Wiatrak, P. (2011). Corn production and plant characteristics response to N fertilization management in dry-land conventional tillage system. International Journal of Plant Production 5 (4), October 2011.

Marra, M.C., Piggott, N.E., & Goodwin, B.K. (2012). The impact of corn rootworm protected biotechnology traits in the United States. AgBioForum, 15(2), 217-230. Available on the World Wide Web: http://www.agbioforum.org/v15n2/v15n2a09-marra.htm

Marra, M.C., Piggott, N.E., & Goodwin, B.K (2010). The anticipated value of SmartStax™ for US corn growers. AgBioForum, 13(1), 1-12. Available on the World Wide Web: http://www.agbioforum.org/v13n1/v13n1a01-marra.htm

National Corn Growers Association (2014). Insect Resistance Management Fact Sheet for Bt Corn. Available on the World Wide Web: http://www.ncga.com/managing-bt-technology

Peairs, F.B., & Pilcher, S.D. (2013). Western Corn Rootworm, Quick Facts. Available on the World Wide Web: http://www.ext.colostate.edu/PUBS/insect/05570.html

Phipps, R.H. & Park, J.R. (2002); Environmental benefits of genetically modified crops: Global and European perspectives on their ability to reduce pesticide use. Journal of Animal and Feed Sciences, 1-18. Available on the World Wide Web: http://cib.org.br/wp-content/uploads/2011/10/estudos_cientificos_ambiental_32.pdf

Shi, Guanming, Chavas, Jean-Paul, & Lauer, Joseph (2013). Commercialized Transgenic Traits, Maize Productivity, and Yield Risk. Nature Biotechnology

(2013) 31 (2): 111-114. Available on the World Wide Web:
http://www.nature.com/nbt/journal/v31/n2/pdf/nbt.2496.pdf

Shi, Guanming, Chavas, Jean-Paul, & Stiegert, Kyle (2010). An Analysis of the Pricing of Traits in the U.S. Corn Seed Market. American Journal of Agricultural Economics (2010) 92 (5): 1324-1338.

Tannura, M. A., S. H. Irwin, and D. L. Good. "Weather, Technology, and Corn and Soybean Yields in the U.S. Corn Belt." Marketing and Outlook Research Report 2008-01, Department of Agricultural and Consumer Economics, University of Illinois at Urbana-Champaign, February 2008. [http://www.farmdoc.uiuc.edu/marketing/morr/morr_archive.html]

University of Minnesota, Minnesota Agricultural Experiment Station (MAES) (2003-2012). Field Crop Trials Results. Available on the World Wide Web: http://www.maes.umn.edu/

US Department of Agriculture (USDA), National Agricultural Statistics Service (NASS). (2014). *Commodity pricing*. Washington, DC: Author. Available on the World Wide Web:
http://www.farmdoc.illinois.edu/manage/uspricehistory/us_price_history.html

USDA NASS. (2014). *Corn Acreage Planted*. Washington, DC: Author. Available on the World Wide Web: http://quickstats.nass.usda.gov/results/E1AC0E4D-095D-3133-91B7-33FA1E08D3FA#9C148F0D-09A6-334B-AC23-390F77FDAD28

USDA NASS. (2014). *Quick stats* [database]. Washington, DC: Author. Available on the World Wide Web: http://www.nass.usda.gov/Quick_Stats/.

Appendices

Appendix A: ANOVA Statistics – Yield Data

This Appendix A contains further details of the multiple linear regressions that were run on the yield dataset, by year. These output tables include standard errors, number of observations, degrees of freedom, and residuals.

Table A-1: ANOVA Summary Statistics for Yield Data, 2003

Regression Statistics	
Multiple R	0.917
R Square	0.841
Adjusted R Square	0.839
Standard Error	13.896
Observations	735

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	9	741994.8	82443.9	427.0	0.000
Residual	725	139988.7	193.1		
Total	734	881983.5			

Table A-2: ANOVA Summary Statistics for Yield Data, 2004

Regression Statistics	
Multiple R	0.892
R Square	0.795
Adjusted R Square	0.793
Standard Error	15.671
Observations	931

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	9	877978.8	97553.2	397.2	0.000
Residual	921	226181.5	245.6		
Total	930	1104160.3			

Table A-3: ANOVA Summary Statistics for Yield Data, 2005

Regression Statistics	
Multiple R	0.792
R Square	0.627
Adjusted R Square	0.623
Standard Error	16.411
Observations	836

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	9	373652.4	41516.9	154.2	0.000
Residual	826	222461.3	269.3		
Total	835	596113.7			

Table A-4: ANOVA Summary Statistics for Yield Data, 2006

Regression Statistics	
Multiple R	0.886
R Square	0.784
Adjusted R Square	0.783
Standard Error	15.737
Observations	1190

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	10	1062016.5	106201.6	428.8	0.000
Residual	1179	291979.7	247.7		
Total	1189	1353996.2			

Table A-5: ANOVA Summary Statistics for Yield Data, 2007

Regression Statistics	
Multiple R	0.808
R Square	0.654
Adjusted R Square	0.651
Standard Error	17.317
Observations	1296

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	10	727202.3	72720.2	242.5	0.000
Residual	1285	385332.0	299.9		
Total	1295	1112534.3			

Table A-6: ANOVA Summary Statistics for Yield Data, 2008

Regression Statistics	
Multiple R	0.838
R Square	0.702
Adjusted R Square	0.699
Standard Error	16.902
Observations	1039

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	10	692511.7	69251.2	242.4	0.000
Residual	1028	293668.6	285.7		
Total	1038	986180.3			

Table A-7: ANOVA Summary Statistics for Yield Data, 2009

Regression Statistics	
Multiple R	0.866
R Square	0.750
Adjusted R Square	0.747
Standard Error	16.071
Observations	940

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	10	718822.0	71882.2	278.3	0.000
Residual	929	239926.7	258.3		
Total	939	958748.7			

Table A-8: ANOVA Summary Statistics for Yield Data, 2010

Regression Statistics	
Multiple R	0.802
R Square	0.643
Adjusted R Square	0.638
Standard Error	13.354
Observations	811

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	12	256224.6	21352.0	119.7	0.000
Residual	798	142312.4	178.3		
Total	810	398537.0			

Table A-9: ANOVA Summary Statistics for Yield Data, 2011

Regression Statistics	
Multiple R	0.775
R Square	0.600
Adjusted R Square	0.593
Standard Error	18.453
Observations	735

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	13	368242.2	28326.3	83.2	0.000
Residual	721	245519.5	340.5		
Total	734	613761.7			

Table A-10: ANOVA Summary Statistics for Yield Data, 2012

Regression Statistics	
Multiple R	0.869
R Square	0.755
Adjusted R Square	0.751
Standard Error	17.846
Observations	673

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	11	648392.4	58944.8	185.1	0.000
Residual	661	210520.9	318.5		
Total	672	858913.3			

Appendix B: ANOVA Statistics – Pricing Data

This Appendix B contains further details of the multiple linear regressions that were run on the pricing dataset, by year. These output tables include standard errors, number of observations, degrees of freedom, and residuals.

Table B-1: ANOVA Summary Statistics for Pricing Data, 2003

Regression Statistics	
Multiple R	0.511
R Square	0.261
Adjusted R Square	-0.016
Standard Error	17.265
Observations	12

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	842.885	280.962	0.943	0.464
Residual	8	2384.624	298.078		
Total	11	3227.509			

Table B-2: ANOVA Summary Statistics for Pricing Data, 2004

Regression Statistics	
Multiple R	0.830
R Square	0.689
Adjusted R Square	0.626
Standard Error	11.332
Observations	19

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	4258.682	1419.561	11.054	0.000
Residual	15	1926.355	128.424		
Total	18	6185.037			

Table B-3: ANOVA Summary Statistics for Pricing Data, 2005

Regression Statistics	
Multiple R	0.685
R Square	0.469
Adjusted R Square	0.381
Standard Error	10.983
Observations	22

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	1920.103	640.034	5.306	0.008
Residual	18	2171.131	120.618		
Total	21	4091.234			

Table B-4: ANOVA Summary Statistics for Pricing Data, 2006

Regression Statistics	
Multiple R	0.833
R Square	0.694
Adjusted R Square	0.654
Standard Error	9.785
Observations	27

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	4994.229	1664.743	17.386	0.000
Residual	23	2202.291	95.752		
Total	26	7196.520			

Table B-5: ANOVA Summary Statistics for Pricing Data, 2007

Regression Statistics	
Multiple R	0.755
R Square	0.570
Adjusted R Square	0.518
Standard Error	9.978
Observations	29

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	3298.824	1099.608	11.045	0.000
Residual	25	2488.974	99.559		
Total	28	5787.798			

Table B-6: ANOVA Summary Statistics for Pricing Data, 2008

Regression Statistics	
Multiple R	0.669
R Square	0.447
Adjusted R Square	0.388
Standard Error	21.580
Observations	32

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	3	10542.195	3514.065	7.546	0.001
Residual	28	13039.451	465.695		
Total	31	23581.646			

Table B-7: ANOVA Summary Statistics for Pricing Data, 2009

Regression Statistics	
Multiple R	0.719
R Square	0.518
Adjusted R Square	0.440
Standard Error	24.819
Observations	30

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	4	16519.421	4129.855	6.705	0.001
Residual	25	15399.444	615.978		
Total	29	31918.865			

Table B-8: ANOVA Summary Statistics for Pricing Data, 2010

Regression Statistics	
Multiple R	0.810
R Square	0.655
Adjusted R Square	0.566
Standard Error	25.153
Observations	30

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	6	27677.396	4612.899	7.291	0.000
Residual	23	14551.359	632.668		
Total	29	42228.755			

Table B-9: ANOVA Summary Statistics for Pricing Data, 2011

Regression Statistics	
Multiple R	0.890
R Square	0.792
Adjusted R Square	0.731
Standard Error	17.082
Observations	32

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	7	26666.097	3809.442	13.055	0.000
Residual	24	7003.220	291.801		
Total	31	33669.317			

Table B-10: ANOVA Summary Statistics for Pricing Data, 2012

Regression Statistics	
Multiple R	0.783
R Square	0.613
Adjusted R Square	0.535
Standard Error	23.020
Observations	43

ANOVA					
	df	*SS*	*MS*	*F*	*Significance F*
Regression	7	29343.944	4191.992	7.910	0.000
Residual	35	18547.877	529.939		
Total	42	47891.821			