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Insurance premiums and GM traits

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Abstract

An argument in favor of the development of genetically modified (GM) hybrids is that their presence is considered to be risk decreasing., and hence, insurance premiums for US corn growers who plant approved hybrids have been reduced. In this study we investigate, using a large set of experimental data, whether the presence in a corn hybrid of various combinations of GM traits is likely to affect production variability and downside risk. We estimate a heteroskedastic production function that allows for the variance of yield to change with the level of inputs, and use the residuals of the mean function to estimate the marginal effect of each input on variance and skewness of yield. The results show that the presence of most combinations of GM traits leads to an increase in both yield variability and downside risk.

Key words: Production functions, yield, risk, skewness, corn, genetically modified traits.

JEL codes: C2, Q12, Q16

Although much attention has been paid to the effect of the introduction of genetically modified (GM) crops (in particular, those with Bt traits) on mean yield, the risk element has received much less attention. Because production risk is a well documented aspect of most types of biological production, a complete evaluation of the impact on production of inputs, and new technologies, requires consideration of their interaction with the riskiness of output, as noted by Shankar, Bennett and Morse (2008). This is particularly important because levels of yield variability and skewness can be influenced by the amount of input use: while some inputs (for example, land size) increase the level of yield variability, others (for example, irrigation, frost protection, disease-resistant seed varieties, and over-capitalization) will reduce variability.

The recognition of this possibility has motivated two lines of research. The first is the theoretical analysis of the effect of specific inputs on yield variability. This discussion is particularly important in the case of agrochemical inputs such as pesticides because it is inconclusive. If, as has been argued, GM traits are to be thought of as more effective pesticides then this discussion carries over to the discussion of the risk impacts of GM traits. We review this literature in the next section. Secondly, because, ultimately, the yield variability effect of specific inputs is an empirical question, there is the need for the definition of an analytical framework that allows for the possibility of risk increasing and risk decreasing inputs in the context of the estimation of production functions. Just and Pope (1978) proposed such an approach, one that allows the identification of the distinction between the effect of an input on the mean function and its effect on output variance.

However, it is also important to take into account the effect of these inputs on downside risk, that is, the probability of being exposed to unexpectedly low returns, since empirical evidence suggests that farmers exhibit decreasing absolute risk aversion, and that their welfare is positively (negatively) affected by an increase (decrease) in skewness of returns (Antle 1987; Kim and Chavas 2003). An increase in skewness of yield means a reduction in downside risk exposure, and skewness may be affected, for example, by chemical applications which may reduce a farmer's risk of extremely low yields (Gallagher 1987). The extension of the Just and Pope approach to higher moments of the distribution (including skewness) was proposed in Antle (1983). Both empirical approaches are briefly reviewed in section 3, while the empirical estimates of the effect of GM traits (and their combinations) on yield variability are presented in section 5. The results suggest that the introduction of GM traits in most combinations has led to an increase in yield variability in corn, and that downside risk has increased, not decreased.

The policy implications of these results, in particular those policies directed to risk management (including insurance), are discussed in section 6 which also concludes.

For example, the Risk Management Agency (RMA), which manages crop insurance in the United States through the Federal Crop Insurance Corporation (FCIC), has agreed to the reduction, by between 14 per cent (for yield risk programs) and 20 per cent (for revenue programs), of insurance premiums for corn growers who plant approved hybrids with GM traits, under the assumption that triple-stacked corn hybrids have a negative effect on yield variability, or a positive effect on the skewness of yield. Whether such an assumption is valid is not *a priori* unanimously accepted and is, ultimately, an empirical question, that we address in this paper.

Insurance, yield variability, pesticides and GM

Production uncertainty has implications for the implementation of crop insurance, and the availability of crop insurance in the USA has depended on ongoing government support, at high cost. We provide a brief background to the program in the next section.

Crop insurance

Crop insurance contracts are developed by the FCIC, and by private sector insurance providers. Private insurance companies sell all Multiple Peril Crop Insurance (MPCI) and FCIC provides subsidized reinsurance to approved commercial insurers (Risk Management Agency 2008). The insurance provider agrees to indemnify the insured farmer against losses due to unavoidable perils, such as unusual climate, insects and disease, inability to plant or excessive loss of quality due to adverse weather during the crop year. Actual Production History (APH) insurance covers between 50 and 85 per cent of the individual grower's yield history (Barnaby 2009), and the producer insures between 55 and 100 per cent of the predicted price. If the harvested amount less any appraised production is less than the yield insured, the producer is paid an indemnity based on the difference (Risk Management Agency 2010). Other products pay indemnities on the basis of low prices, low yields, or both. Growers may also select catastrophic (CAT) coverage (Barnaby 2009).

Table 1. Insurance Statistics for Corn Compared with Total Crops

Total Crop Year Statistics as of 31 January 2011					Corn Year Statistics as of 31 January 2011			
Item	**1990**	**1999**	**2009**		**Item**	**1990**	**1999**	**2009**
	Number ('000)					Number ('000)		
Policies	895	1288	1171		Policies	295	451	504
Net acres insured	101361	196918	264621		Net acres insured	26304	52472	71893
						Percent		
					Insured acres as percentage of total acres planted to corn	35	67	83
	Billion dollars					Billion dollars		
Farmer paid premium	0.62	1.35	3.52		Farmer paid premium	0.16	0.4	1.36
Premium subsidies	0.22	0.95	3.82		Premium subsidies	0.05	0.2	2.04
Total premium	0.84	2.3	8.95		Total premium	0.21	0.6	3.4
Indemnities	0.97	2.43	5.43		Indemnities	0.12	0.36	1.18
Insurance protection	12.83	30.94	79.5		Insurance protection	4.04	8.6	31.1
	Percent					Percent		
Loss ratio	116	105	58		Loss ratio	55	60	35
Loss ratio excluding subsidy	156	180	154		Loss ratio excluding subsidy	75	90	87

Sources: USDA NASS (2011); Risk Management Agency (2011)

Some statistics comparing the insurance performance of corn with other crops are provided in table 1. For unsubsidized insurance to be viable, loss ratios (ratio of indemnities to premium payments) need to be no more than 0.7 (Wright and Hewitt 1994). However, to encourage participation, the Federal Crop Insurance Act of 1980 authorized a subsidy of 30% of the crop insurance premium limited to the dollar amount of 65% coverage, so that the objective is that pre subsidy premiums should be set at a level such that the loss ratio is 1.075 (Babcock, Hart and Hayes 2004). Over the 1980s and early 1990s the actuarial performance of the program was poor, but, following improvement in participation rates, the aggregate loss ratio fell to 0.98 for 1994-2003, compared with over 1.5 in1981-1993 (Glauber 2004). The loss ratio has continued to improve, particularly for corn.

Despite the program's actuarial performance having become more acceptable, there is still concern about the large underwriting gains that private insurance companies earn under the program (Glauber 2004; LaFrance, Pope and Tack 2010), and the average annual cost to government of the whole program which, for the crop years 2002-2010, and excluding premiums, was $4.12 billion (Risk Management Agency 2011).

If premiums are reduced, and risk (measured in terms of variance and skewness) can be shown to have increased (or not changed), the loss ratio could be expected to increase, particularly since Goodwin, Vandeveer and Deal (2004) find a negative relationship between premium rates and level of participation. However it should also be noted that previous studies (Goodwin 1993; Knight and Coble 1997) have shown that demand for crop insurance is generally inelastic with respect to premium so the effect of the reductions on uptake of insurance may, in fact, be relatively small.

Yield variability, pesticides and GM

Bt corn is genetically engineered to produce a protein found in the soil bacterium *Bacillus thuringiensis*. The protein is toxic to lepidopterous insects (Hurley, Mitchell and Rice 2004). The most economically important pests of corn are the European corn borer and corn rootworm. Applications of foliar insecticide to control corn borer infestations provide protection of up to 80% against first generation corn borer, and 67% against second generation borer (Mason et al. 1996; Ostlie, Hutchison and Hellmich 1997; Gray and Steffey 1999; Baute, Sears and Schaafsma 2002). Corn rootworm was managed historically by rotating crops or with soil insecticide, but since some species of rootworm have evolved to reduce the effectiveness of crop rotation in some areas, and soil insecticide is not entirely effective, protection against rootworm through traditional methods is estimated at about 63% (Rice 2004). A non-zero pest infestation causes some pest damage, and realized yield adjusts downward, being lower than potential yield.

However if the Bt traits are present, the control of both pests could be considered to be close to 100% (Rice and Pilcher 1998; Ortman et al. 2001; Baute, Sears and Schaafsma 2002; Singer, Taylor and Bamka 2003; Dillehay et al. 2004; Rice 2004).

The Bt traits in corn hybrids can therefore be classified as a kind of "super pesticide", and are likely to have a positive effect on expected yield. They may also have an effect on yield variability, although there is less consensus in the literature, about the effect on yield variability of agrochemicals such as pesticide and fertilizer than there is about other inputs. Therefore, the marginal effect on yield variability for these inputs (the traits incorporated in the seeds) could be expected to be negative or positive, respectively, according to the differing views expressed by, for example, Feder (1979) and others on one hand and Horowitz and Lichtenberg (1993)and Pannell (1991) on the other.

Feder (1979) is considered to have established the theoretical relationship for the presumed negative relationship between degree of variability and level of pesticide usage. The number of pests (or its distribution) within a given time period can be reduced by using pesticides, and in fact a major motivation for pesticide application is the provision of some insurance against damage. The existence of uncertainty in the pest-pesticide system leads to a higher and more frequent use of chemicals and Feder (1979) argues that such an increase in use will lead to a reduction in marginal variance. As empirical evidence in support of this reasoning, Turpin and Maxwell (1976) show that farmers use soil pesticides as insurance against production uncertainty, suggesting that they perceive that increasing input use does not increase variance. Smith and Goodwin (1996) find that crop insurance and pesticide are substitutes, so that an increase in the use of pesticides reduces the requirement for crop insurance.

Pannell (1991) suggests that the reputation of pesticides as risk reducing inputs appears to be mainly based on analyses which only consider uncertainty about the level of pest infestation or chemical efficacy, and not the many other sources, such as uncertainty about output price and yield, which may or may not result in reduced risk as pesticide use is increased. Horowitz and Lichtenberg (1993) argue that, intuitively, an input reduces variability if it adds more to output in bad states of nature than in good states of nature, since this makes output in each state of nature more uniform. An input increases variability if it adds relatively more to output in good states than in bad ones, since that increases the discrepancy between states of nature. In crops where high pest infestations occur primarily when crop growth conditions are good, pesticides work by increasing output in good states of nature and marginal variance is likely to be positive (Horowitz and Lichtenberg 1993).

The conclusions of Pannell (1991) and Horowitz and Lichtenberg (1993) differ from the conventional wisdom because they consider output uncertainty rather than concentrating solely on pest infestation. Pesticides are likely to increase yield variability when output uncertainty is the dominant source of randomness (Pannell 1991).[2]

Empirical approach: stochastic production functions

An understanding of the marginal effects of input use on the distribution of output is essential to the understanding of the relationship between input use and yield variability. The starting point of much of the literature that analyses this relation in the context of the estimation of production functions is the work of Just and Pope (1978; 1979), who argue that popular formulations of stochastic production functions are limited in their analysis, in that the choice of functional form (where the error term interacts multiplicatively with

[2] Much of this discussion carries over to other agrochemical inputs, namely fertilizer. While Glauber and Collins (2002), for example, state that it is a known fact that pesticides and fertilizer reduce risk, others (for example, Just and Pope 1978; Wan, Griffiths and Anderson 1992) suggest that fertilizer use may lead to increased yield variability and Quiggin (1992) suggests that fertilizer may be risk increasing in the sense that their marginal productivity may be negative in a poor state of nature and positive in a good state of nature.

the deterministic part) imposes a risk-increasing effect for all inputs, whereas there are cases where inputs may reduce output variance.

Just and Pope (1978; 1979) propose instead that a useful production function should have sufficient flexibility so that the effect of inputs on the deterministic component of production may differ from the effect of inputs on the stochastic component. They suggest instead that the error term should be parameterized by some function of the inputs, *h(X)*, in such a way that the relationship of the inputs with risk is not determined solely by the relationships of inputs with expected output.[3] In the most general case, the disturbance *h(X)ε* enters the production function in an additive way, allowing for the possibility of increasing, decreasing or constant marginal risk (Just and Pope 1978). Such a function can be expressed as follows:

(1) $$Y_{it} = f(X_{it}) + u_{it} = f(X_{it}) + h^{1/2}(Z_{it})\, \varepsilon_{it}$$

where Y_{it} is output and we assume that $E(\varepsilon_{it}) = 0$, $var(\varepsilon_{it}) = 1$.[4] The functions $f(X_{it})$ and $h(Z_{it})$ determine the conditional mean and variance, respectively, of Y. The component f(.) is the deterministic component of production (representing the mean of production) as a function of the independent variables and u_{it} is the stochastic component (representing its variance). The suggested approach is flexible in that the set of inputs used to estimate the stochastic component of the production function (Z_{it}), need not be the same as the set of inputs in the deterministic part of the production function (X_{it}), and the functional form of h(.), may or may not be identical to that of f(.).

While the Just and Pope (1978) production function allows input levels to affect risk (defined as the variance of output) independently of their effect on the expected level of output, later studies have suggested the need to understand the relation between the

[3] Their model, with interdependent heteroskedastic disturbances that condition the mean and variance of the dependent variable on independent variables, uses the heteroskedastic error structure proposed by Harvey (1976).

[4] The multiplicative case, *y=f(X)h(X)ε* constrains the sign of the change in variance of marginal product with respect to a factor change without consideration of the nature of the input.

use of variable inputs and higher moments of the distribution of output (Babcock, Chalfant and Collender 1987). For example, Day (1965), Anderson (1973), Antle and Goodger (1984), and Just and Pope (1979) found that third and fourth moments of output may be functions of inputs. Nelson and Preckel (1989) identified the need for a flexible approach to estimating yield distributions when skewness is important, and Antle and Goodger (1984) found that input-conditioned mean and variance are not sufficient for a description of a stochastic production.

Antle (1983) suggested an extension of the approach proposed by Just and Pope (1978) which a general representation of the distribution of output without imposing arbitrary restriction on the moments and showed that consistent estimates of all central moments can be obtained econometrically. In this model, the moments of the probability distribution, including skewness, are explicit functions of inputs, allowing for an analysis of the effect of input use on downside risk exposure (Kim and Chavas 2003). Following Kim and Chavas (2003), $E[y_{it} - E(y_{it})]^j$ is the jth central moment of y_{it}. The skewness is therefore the cube of the residuals of yield, and the marginal skewness conditional on the input is the cube of the residuals regressed on the inputs.

Data

In this study we use a large dataset of results from experimental field trials to investigate the effects of the presence in a corn hybrid of a GM trait, or a combination of GM traits on variance and skewness of yield. Our dataset was compiled from reports of actual yield results from independently run experimental field trials of corn hybrids, submitted by corn breeders to the State Agricultural Extension Services of ten universities (Illinois at Urbana-Champaign, Purdue, Iowa State, Kansas State, Minnesota, Missouri, Nebraska – Lincoln, The Ohio State, South Dakota State, and Wisconsin – Madison) over 13 years, in the ten most important corn-producing states in the United States. While data for 13 years would represent a small sample for an individual farmer, we have the advantage of data from trials for those 13 years at a large number of locations. In all we have 1765 individual trials over a range of conditions.

There are several advantages in using these data to estimate the effect of GM traits, on the yield distribution. The trials were designed and managed with the objective of determining the productive value of each hybrid, and hence, we can consistently estimate the genetic value of the hybrid (including the presence of GM traits) in terms of its effect on yield. The trial reports provide details of the agronomic practices adopted in the tests, allowing us to avoid the identification problems that are associated with the estimation of production functions and recognized in the literature (Peterson and Hayami 1977; Babcock and Foster 1991; Griliches and Mairesse 1998; Just and Pope 2001; Mundlak 2001). The included

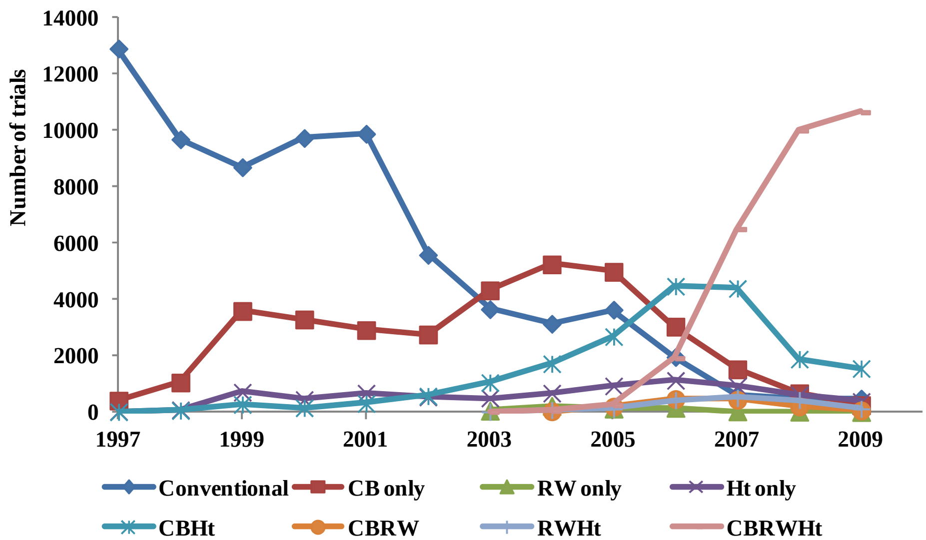

Figure 1. Number of trials by year and GM category

variables are defined in table 3, and there is a more detailed description in the appendix. The data consist of real results for yield in different locations over the ten most important corn-producing states of the USA, and over a relatively long period (13 years), and we therefore avoid problems with using aggregate data (Eisgruber and Schuman 1963;

Brennan 1984; Kolady and Lesser 2009). The results are published and provide a source of objective information, thus benefiting from the independence of the university system.

Another important advantage of our dataset is that because we use experimental data, our analysis is independent of the risk preferences of an individual farmer. Therefore, while the analysis will not directly reflect decision making at farm level, it will allow the focus to be instead on variability and skewness. It should also be noted that at the farm level production there is a non-zero probability of a zero yield. However, the results of the trials from which we source our data are reported only where a non-zero yield has been achieved. Therefore an advantage of using this experimental data is that the distribution of the yield is relatively normal around a mean of 181 bushels/acre, and is not truncated at, or near, zero.

The data reports yield in bushels per acre for 163,941 observations for 14,614 hybrids, at 339 locations. In addition to information about the genetic make-up of the hybrid (including the traits present in each hybrid and the degree of stacking), the dataset includes rich detail on agronomic practices (yield, seeding rate, nitrogen application), climatic conditions (rainfall and average minimum and maximum temperatures for each of the months April to September) as well as other variables that potentially influence yield and its variability (soil type, cultivation type, previous crop, whether the trial is early or late, and whether or not irrigation water was applied).

The specific detail of pesticide and herbicide management practices at each site varies quite considerably between sites and over years, and we have not been able to include specific practices. We also do not have information about the incidence of pest infestation. We have therefore included interaction terms for year by Crop Reporting District, and we believe that year and location effects relating to pest infestations and chemical use will be captured by these variables.

Table 3. Summary Statistics

Variable	Definition	Mean	Std. Dev.	Min	Max
Yield	Bushels per acre of shelled grain (56lb/bu)adjusted to a moisture content of 15.5%	181.33	39.96	1	317
Plant density	Plant density in thousands of kernels per acre	29.40	3.48	8.65	43.47
No or min till	Dummy variable indicating no or minimum till	0.08	0.28	0	1
Conventional	Conventional soil preparation methods (base case)	0.92	0.28	0	1
Irrigated	Dummy variable indicating crop grown with irrigation	0.13	0.34	0	1
Dryland	Crop grown without irrigation (base case)	0.87	0.34	0	1
Early	Dummy variable indicating an early trial	0.23	0.42	0	1
Late	Dummy variable indicating a late trial (base case)	0.77	0.42	0	1
Soybean	Dummy variable indicating that soybean was the previous crop in the rotation (base case)	0.83	0.38	0	1
Corn	Dummy variable to indicating that corn was the previous crop in the rotation	0.08	0.27	0	1
Wheat	Dummy variable to indicating that wheat was the previous crop in the rotation	0.05	0.22	0	1
Alfalfa	Dummy variable to indicating that alfalfa was the previous crop in the rotation	0.01	0.12	0	1
Other	Dummy variable to indicating that a crop other than those mentioned above was the previous crop in the rotation	0.03	0.16	0	1
Silt loam	Dummy variable indicating silt loam soil (base case)	0.56	0.50	0	1
Clay	Dummy variable indicating clay soil	0.02	0.15	0	1
Silty clay loam	Dummy variable indicating Silty clay loam soil	0.18	0.39	0	1
Clay loam	Dummy variable indicating Clay loam soil	0.10	0.30	0	1
Loam	Dummy variable indicating Loam	0.08	0.27	0	1
Sandy loam	Dummy variable indicating Sandy loam soil	0.05	0.23	0	1
Sand	Dummy variable indicating Sand	0.00	0.06	0	1
Nitrogen (lbs /ac)	Nitrogen application in lbs per acre	141.54	76.92	0	380
Nitrogen not reported	Dummy variable indicating that nitrogen use was not reported	0.15	0.36	0	1
Conventional	Dummy variable indicating conventional hybrids (base case)	0.43	0.49	0	1
CB	Dummy variable indicating hybrid has corn borer resistant trait only	0.21	0.41	0	1
RW	Dummy variable indicating hybrid has corn rootworm resistant trait only	0.00	0.05	0	1
Ht	Dummy variable indicating hybrid has herbicide tolerant trait only	0.04	0.20	0	1
CB and Ht	Dummy variable indicating hybrid has both corn borer resistant and herbicide tolerant traits	0.11	0.32	0	1
RW and Ht	Dummy variable indicating hybrid has both corn rootworm resistant and herbicide tolerant traits	0.01	0.10	0	1
CB and RW	Dummy variable indicating hybrid has both corn borer resistant and corn rootworm resistant traits	0.01	0.09	0	1
CB, RW and Ht	Dummy variable indicating hybrid is at least triple stacked with corn borer resistant, corn rootworm resistant and herbicide tolerant traits	0.19	0.39	0	1

A detailed description of the data, their sources and our methods for dealing with missing data can be found in the appendix. Figure 1 summarizes the relative importance of GM versus non GM varieties under trial. The breakdown of data by year and state of trial, and by year and GM attributes, can also be found in tables 5 and 6 in the appendix.

Empirical estimates

We investigate the effect of the presence of GM traits on the distribution of corn yield through the specification and estimation of a heteroskedastic production function that allows for the variance and skewness of yield to change with the presence of the traits and their various combinations (Just and Pope 1978; 1979; Anderson and Griffiths 1981). Using the approach proposed by Just and Pope (1978) and Antle (1983), we start by obtaining consistent estimates of the mean function for corn yield. Because we have multiple observations for the same hybrids, we are also able to control for varietal differences and, in addition, we take advantage of the richness of the data to control for a wide variety of agronomic practices, location characteristics and climatic conditions. We estimate a linear production function and include only observations for hybrids for which we have at least five trials.[5] Because our main concern, in this first stage, is to obtain consistent estimates of the mean, we use a fixed effects specification of this production function

(2) $y_{it} = x'_{it}\beta + \alpha_i + \mu_{it}$

[5] We therefore base our analysis on a sample of 147,790 observations relating to 8,423 hybrids. The summary statistics of the included variables are presented in table 3.

where y_{it} is the yield, adjusted for moisture content, of hybrid i in year t, x'_{it} is the set of covariates presented in table 3, together with a set of location and year dummy variables (or their interactions) that account, respectively, for any location specific trial characteristics and year specific occurrences that were not accounted for elsewhere in the data, α_i is the unobserved effect of the underlying germplasm and μ_{it} is the idiosyncratic error relating to both the cross sectional element and time.

The residuals are then generated by subtracting the linear estimates of yield from observed yield and squared (cubed) to give the variance (skewness) of yield, which are then explained as a function of the independent variables, including the GM traits and their combinations. In the first step we were interested only in generating the residuals, and therefore the fixed effects model was suitable for our needs. However, we now wish to obtain the marginal effect of the GM traits and their combinations, on variance and skewness, and in the fixed effects estimation these effects are absorbed into the unobserved effects for each hybrid.

One alternative would be to estimate the random effects model shown in equation (3), where $GM'\gamma$ is the effect of the GM traits, θ_i the underlying genetics of each hybrid, and $\alpha_{i.} = GM'\gamma + \theta_i$.

(3) $y_{it} = x'_{it}\beta + GM'\gamma + \theta_i + \mu_{it}$

However, when entering hybrids for trial, plant breeders can be expected to nominate trial sites with conditions that are favorable for the performance of each hybrid. It is therefore likely that there will be some correlation between the characteristics of the trial site and those of the individual hybrid. To overcome potential problems of endogeneity with the random effects model, we can estimate equation (3) using the approach proposed by Hausman and Taylor (1981). The Hausman-Taylor estimator fits a random effects model in which some of the covariates are correlated with the unobserved individual level random effect but none of the explanatory variables are correlated with the idiosyncratic error, μ_{it}. Given the richness of our dataset this seems a credible assumption. Following Greene (2003) we rewrite equation (3) using three sets of observed variables to express this estimator:

(4) $y_{it} = x'_{1it}\beta_1 + x'_{2it}\beta_2 + z'_{1i}\gamma_1 + \theta_i + \mu_{it}$

where x_{1it} is a matrix of variables that are time varying and uncorrelated with $\theta_{i,}$ (for example those trial characteristics not under the control of the seed breeder), x_{2it} is a matrix of variables that are time varying and are correlated with $\theta_{i,}$ (for example those trial characteristics known in advance by the breeder, and related with the location of the trial) and z_{1i} is a matrix of variables that are time invariant and uncorrelated with θ_i (in this case, the various combinations of GM traits).

Under the standard assumptions outlined by Greene (2003, p. 303), Hausman and Taylor (1981) show that x_{1it}, $z_{1i,}$ x_{2it} - $\bar{x}_{2i}$ and $\bar{x}_{1i}$ can be used as instrumental variables in the estimation of equation (3). The Hausman-Taylor approach allows identification and efficient estimation of both β and θ_i, performs better than traditional instrumental variables methods, which rely on excluded exogenous variables for instruments, and has the strong advantage of not needing external instruments (Verbeek 2008).

Therefore, by regressing the variance (skewness) on the inputs, using the Hausman-Taylor estimator, we find the marginal effect of each input on the variance (skewness) while addressing any problems of endogeneity between the hybrid effects and the variance (skewness) of the distribution. Additionally, the use of this estimator allows us to include the interaction term between CRD and year (which we use as a proxy for pest pressure and pesticide use) as an additional control.[6] The empirical estimates are presented in table 4.[7]
The full results are reported in table 8 in the appendix.

The results of the regressions for the second and third moments show that increased nitrogen application, consistent with Glauber and Collins (2002), but contrary to the findings of Just and Pope (1978) and Wan, Griffiths and Anderson (1992), decreases variance. There is no statistically significant effect of fertilizer use on downside risk. Irrigation reduces yield variability, and strongly reduces the downside risk. This is consistent with, the literature, for example, the findings of Harri et al. (2009).

[6] We have also estimated the marginal variance and skewness using FGLS, but because of problems with computer capacity we were not able to include the interaction term which proxies for pest pressure.

[7] We also present, in table 4, for information, the results that would have been obtained if we had used the Hausman-Taylor estimator rather than the fixed effects estimator to generate the residuals in the first step. The results are almost identical.

Table 4. Empirical estimates of the effect of input use of variance and skewness of output

VARIABLES	Model 1 Variance (based on FE residuals)	Model 2 Skewness (based on FE residuals)	Model 3 Variance (based on HT residuals)	Model 4 Skewness (based on HT residuals)
GM traits (Conventional as base)				
Corn borer resistance (CB)	86.44***	-3,225***	82.86***	-2,982***
	-14.72	-1,021	-14.64	-1,018
Rootworm resistance (RW)	-17.74	1,648	-16.46	1,472
	-71.82	-5,727	-71.49	-5,710
Herbicide tolerance (Ht)	41.37*	-1,426	44.17*	-1,682
	-24.73	-1,823	-24.61	-1,818
CB and Ht	141.0***	-6,256***	139.5***	-6,442***
	-21.5	-1,731	-21.42	-1,726
CB and RW	289.1***	-9,006***	289.2***	-9,389***
	-49.04	-3,407	-48.78	-3,398
RW and Ht	181.5***	-4,572	177.3***	-5,418
	-50.38	-3,651	-50.13	-3,640
CB, RW and Ht	97.95***	-5,342**	94.21***	-5,760**
	-25.85	-2,244	-25.79	-2,237
Plant density	-1.431	-1,076***	-0.0708	-1,175***
	-2.098	-257.7	-2.101	-256.9
No min till	43.96***	-1,481	37.78**	-1,304
	-15.94	-1,958	-15.96	-1,952
Irrigated	-92.82***	10,972***	-95.11***	11,454***
	-20.55	-2,523	-20.58	-2,515
Early	-56.32***	1,798	-58.54***	1,512
	-9.469	-1,093	-9.475	-1,090
Previous crop: Corn	169.4***	-11,288***	166.2***	-11,638***
	-14.32	-1,755	-14.33	-1,750
Previous crop: Wheat	199.2***	-11,310***	201.5***	-10,985***
	-20.15	-2,473	-20.17	-2,466
Previous crop: Alfalfa	108.6***	-1,883	95.81***	-772.9
	-27.29	-3,348	-27.32	-3,338
Previous crop: Other	347.4***	-24,428***	337.7***	-23,819***
	-29.21	-3,586	-29.25	-3,575
Nitrogen in lbs/ac	-0.603***	11.34	-0.541***	9.472
	-0.121	-14.86	-0.121	-14.82
Soil type: Clay	204.9***	-2,333	212.8***	-2,414
	-57.05	-7,007	-57.12	-6,987
Soil type: Silty clay loam	-97.20***	5,465***	-94.94***	5,393***
	-11.35	-1,392	-11.36	-1,388
Soil type: Clay loam	-133.3***	2,930	-141.1***	3,113*
	-15.31	-1,878	-15.32	-1,873
Soil type: Loam	-42.10**	-1,472	-33.35*	-1,578
	-18.8	-2,308	-18.82	-2,301
Soil type: Sandy loam	364.2***	-17,917***	383.4***	-19,377***
	-18.66	-2,292	-18.69	-2,285
Soil type: Sand	657.9***	-13,935**	695.4***	-17,436***
	-55.23	-6,782	-55.3	-6,762
Constant	-1,164**	178,162***	-1,437***	194,387***
	-538.1	-66,016	-538.7	-65,825
Observations	147,790	147,790	147,790	147,790
Number of hybrids	8,423	8,423	8,423	8,423

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

The estimates for our main results of interest show that the marginal variance for most GM traits and their combinations is positive, and therefore the presence of GM leads to an increase in variance, except in the case of the presence of rootworm by itself which has no significant effect.[8] A more surprising result, given the policy of discounting insurance premiums when triple stacked hybrids are planted, is that the presence of triple stacked traits increases variance. Finally, and if we assume that downside risk is an important aspect, it is worth noting that in the skewness function, most of the GM trait combinations (including the triple stacking of traits), have a statistically significant negative coefficient. Therefore, the effect on downside risk is negative and strongly statistically significant except in the cases of the rootworm resistance trait when it is present by itself, herbicide tolerance by itself, and the rootworm/herbicide tolerant combination, all of which have no statistically significant effect. These results suggest that if the reduction in insurance premiums is guided by a supposed reduction in variability of yields, then the reduction cannot be justified.

Conclusion

In this paper we use a large, rich dataset collated from the results of experimental hybrid corn trials by 10 US university extension services in the most important corn-producing states in the US over 13 years to investigate the effects on variability of yield and downside risk of the presence of GM traits. Following the approaches of Just and Pope (1979) and Antle (1983), we use the residuals obtained from the estimation of a linear production function to calculate the variance and skewness of yield, conditional on the inputs, including the various

[8] Recall that hybrids having only the rootworm trait make up only a very small proportion of our sample (table X).

combinations of GM corn. Our most interesting finding is that the presence of most combinations of GM traits leads to an increase in variance and an increase in downside risk. Since the reduction in risk premiums applies only to hybrids which have at least three of the GM traits, we are most interested in the result for the triple stacked hybrids. We find that the presence of triple stacking has a strongly statistically significant positive effect on variance, and an equally strongly significant negative effect on skewness. We therefore conclude that, based on our sample of hybrids, if the FCIC's policy of a reduction in insurance premiums is guided either by a supposed reduction in variability of yields or an improvement in downside risk for growers who plant triple stacked hybrids, then the reduction cannot be justified.

References

Anderson, J. R. 1973. Sparse Data, Climatic Variability, and Yield Uncertainty in Response Analysis. *American Journal of Agricultural Economics* 55(1): 77-82.

Anderson, J. R., and W. E. Griffiths. 1981. Production Risk and input use: pastoral zone of Eastern Australia. *Australian Journal of Agricultural Economics* 25(2): 149-159.

Antle, J. M. 1987. Econometric Estimation of Producers' Risk Attitudes. *American Journal of Agricultural Economics* 69(3): 509-522.

Antle, J. M. 1983. Testing the Stochastic Structure of Production: A Flexible Moment-Based Approach. *Journal of Business & Economic Statistics* 1(3): 192-201.

Antle, J. M., and W. J. Goodger. 1984. Measuring Stochastic Technology: The Case of Tulare Milk Production. *American Journal of Agricultural Economics* 66(3): 342-350.

Babcock, B. A., J. A. Chalfant, and R. N. Collender. 1987. Simultaneous Input Demands and Land Allocation in Agricultural Production Under Uncertainty. *Western Journal of Agricultural Economics* 12: 207-215.

Babcock, B. A., and W. E. Foster. 1991. Measuring the Potential Contribution of Plant Breeding to Crop Yields: Flue-Cured Tobacco, 1954-87. *American Journal of Agricultural Economics* 73(3): 850-859.

Babcock, B. A., C. E. Hart, and D. J. Hayes. 2004. Actuarial Fairness of Crop Insurance Rates with Constant Rate Relativities. *American Journal of Agricultural Economics* 86(3): 563-575.

Barnaby, G. A. 2009. *Actual production History - Crop Insurance*. Farm Management Guide. MF-907 Kansas State University Agricultural Experimetn Station and Cooperative Extension Service, Available at www.ksre.ksu.edu/library/agec2/mf907.pdf: www.ksre.ksu.edu/library/agec2/mf907.pdf. Accessed on 28 January 2011.

Baute, T. S., M. K. Sears, and A. W. Schaafsma. 2002. Use of Transgenic Bacillus thuringiensis Berliner Corn Hybrids to Determine the Direct Economic Impact of the European Corn Borer (Lepidoptera: Crambidae) on Field Corn in Eastern Canada. *Journal of Economic Entomology* 95(1): 57-64.

Brennan, J. P. 1984. Measuring the Contribution of New Varieties to Increasing Wheat Yields. *Review of Marketing and Agricultural Economics* 52(3): 175-195.

Day, R. H. 1965. Probability Distributions of Field Crop Yields. *Journal of Farm Economics* 47(3): 713-741.

Dillehay, B. L., G. W. Roth, D. D. Calvin, R. J. Kratochvil, G. A. Kuldau, and J. A. Hyde. 2004. Performance of Bt Corn Hybrids, their Near Isolines, and Leading Corn Hybrids in Pennsylvania and Maryland. *Agronomy Journal* 96(3): 818-824.

Eisgruber, L. M., and L. S. Schuman. 1963. The Usefulness of Aggregated Data in the Analysis of Farm Income Variability and Resource Allocation. *Journal of Farm Economics* 45(3): 587-591.

Feder, G. 1979. Pesticides, Information, and Pest Management under Uncertainty. *American Journal of Agricultural Economics* 61(1): 97-103.

Gallagher, P. 1987. U.S. Soybean Yields: Estimation and Forecasting with Nonsymmetric Disturbances. *American Journal of Agricultural Economics* 69(4): 796-803.

Glauber, J. W. 2004. Crop Insurance Reconsidered. *American Journal of Agricultural Economics* 86(5): 1179-1195.

Glauber, J. W., and K. Collins. 2002. Crop Insurance, Disaster Assistance, and the Role of the Federal Government in Providing Catastrophic Risk Insurance. *Agricultural Finance Review* 62(1): 81-101.

Goodwin, B. K. 1993. An Empirical Analysis of the Demand for Multiple Peril Crop Insurance. *American Journal of Agricultural Economics* 75(2): 425-434.

Goodwin, B. K., M. L. Vandeveer, and J. L. Deal. 2004. An Empirical Analysis of Acreage Effects of Participation in the Federal Crop Insurance Program. *American Journal of Agricultural Economics* 86(4): 1058-1077.

Gray, M. E., and K. L. Steffey. 1999. *1999 Illinois Agricultural Pest Management Handbook*. University of Illinois Extension, Available at

Greene, W. H. 2003. *Econometric Analysis*. Upper Saddle River, New Jersey: Prentice Hall.

Griliches, Z., and J. Mairesse 1998. Production functions: the search for identification. In Z. Griliches, ed. *Practicing Econometrics: Essays in Method and Application*. Northampton, MA: Edward Elgar.

Harri, A., C. Erdem, K. H. Coble, and T. O. Knight. 2009. Crop Yield Distributions: A Reconciliation of Previous Research and Statistical Tests for Normality. *Review of Agricultural Economics* 31(1): 163-182.

Harvey, A. C. 1976. Estimating Regression Models with Multiplicative Heteroscedasticity. *Econometrica* 44(3): 461-465.

Hausman, J. A., and W. Taylor. 1981. Panel Data and Unobservable Individual Effects. *Econometrica* 49(6): 1377-1398.

Horowitz, J. K., and E. Lichtenberg. 1993. Insurance, Moral Hazard, and Chemical Use in Agriculture. *American Journal of Agricultural Economics* 75(4): 926-935.

Hurley, T. M., P. D. Mitchell, and M. Rice. 2004. Risk and the Value of Bt Corn. *American Journal of Agricultural Economics* 86(2): 345-358.

Just, R. E., and R. D. Pope 2001. Chapter 12 The agricultural producer: Theory and statistical measurement. In B. Gardner, and G. Rausser, ed. *Handbook of Agricultural Economics*. Volume 1, Part A: Elsevier, pp. 629-741.

Just, R. E., and R. D. Pope. 1979. Production Function Estimation and Related Risk Considerations. *American Journal of Agricultural Economics* 61(2): 276-284.

Just, R. E., and R. D. Pope. 1978. Stochastic specification of production functions and economic implications. *Journal of Econometrics* 7(1): 67-86.

Kim, K., and J.-P. Chavas. 2003. Technological change and risk management: an application to the economics of corn production. *Agricultural Economics* 29(2): 125-142.

Knight, T. O., and K. H. Coble. 1997. Survey of U.S. Multiple Peril Crop Insurance Literature since 1980. *Review of Agricultural Economics* 19(1): 128-156.

Kolady, D. E., and W. Lesser. 2009. But are they Meritorious? Genetic Productivity Gains under Plant Intellectual Property Rights. *Journal of Agricultural Economics* 60(1): 62-79.

LaFrance, J., R. D. Pope, and J. Tack 2010. Risk Response in Agriculture. In J. Ziven, and J. M. Perloff, ed. *Agricultural Policy and the Economics of Biofuels, :*. Chicago: National Bureau of Economic Research and the University of Chicago Press.

Mason, C., M. Rice, D. D. Calvin, J. Van Duyn, W. D. Showers, W. D. Hutchison, J. Witkowski, R. A. Higgins, D. W. Onstad, and G. P. Dively. 1996. *European Corn Borer: Ecology and Management*. North Regional Extension Publication. No. 327 Iowa State University. , Ames, Iowa.

Mundlak, Y. 2001. Chapter 1 Production and supply. In B. Gardner, and G. Rausser, ed. *Handbook of Agricultural Economics*. Volume 1, Part A: Elsevier, pp. 3-85.

Nelson, C. H., and P. V. Preckel. 1989. The Conditional Beta Distribution as a Stochastic Production Function. *American Journal of Agricultural Economics* 71(2): 370-378.

Ortman, E. E., B. D. Barry, L. L. Buschman, D. D. Calvin, J. Carpenter, G. P. Dively, J. E. Foster, B. W. Fuller, R. L. Hellmich, R. A. Higgins, T. E. Hunt, G. P. Munkvold, K. R. Ostlie, M. E. Rice, R. T. Roush, M. K. Sears, A. M. Shelton, B. D. Siegfried, P. E. Sloderbeck, K. L. Steffey, F. T. Turpin, J. L. Wedberg, and J. J. Obrycki. 2001. Transgenic Insecticidal Corn: The Agronomic and Ecological Rationale for Its Use. *BioScience* 51(11): 900-905.

Ostlie, K. R., W. D. Hutchison, and R. L. Hellmich. 1997. *Bt Corn and European Corn Borer*. NCR Publication. 602 University of Minnesota, St Paul.

Pannell, D. 1991. Pests and pesticides, risk and risk aversion. *Agricultural Economics* 5(4): 361-383.

Peterson, W., and Y. Hayami 1977. Technical Change in Agriculture. In L. Martin, ed. *A Survey of Agricultural Economics Literature*. 1. Minneapolis: University of Minnesota Press, pp. 497-540.

Quiggin, J. 1992. Some observations on insurance, bankruptcy and input demand. *Journal of Economic Behavior and Organization* 18(1): 101-110.

Rice, M. 2004. Transgenic Rootworm Corn: Assessing Potential Agronomic, Economic and Environmental Benefits. *Plant Management Network*.

Rice, M., and C. D. Pilcher. 1998. Potential benefits and limitations of transgenic Bt corn for management of the European corn borer (Lepdoptera: Crambidae). *American Entomologist* 44(1): 75-78.

Risk Management Agency. 2010. Crop Policies and Pilots. Available at http://www.rma.usda.gov/policies/. Accessed on 24 September 2010.

Risk Management Agency. 2008. A History of the Crop Insurance Program. Available at http://www.rma.usda.gov/aboutrma/what/history.html.

Risk Management Agency. 2011. Program Costs and Outlays. Available at http://www.rma.usda.gov/aboutrma/budget/costsoutlays.html.

Shankar, B., R. Bennett, and S. Morse. 2008. Production risk, pesticide use and GM crop technology in South Africa. *Applied Economics* 40(19): 2489-2500.

Singer, J. W., R. W. Taylor, and W. J. Bamka. 2003. Corn Yield Response of Bt and Near-Isolines to Plant Density. *Crop Management Online*.

Smith, V. H., and B. K. Goodwin. 1996. Crop Insurance, Moral Hazard, and Agricultural Chemical Use. *American Journal of Agricultural Economics* 78(2): 428-438.

Turpin, F., and J. Maxwell. 1976. Decision-making Related to Use of Soil Insecticides by Indiana Corn Farmers. *Journal of Economic Entomology* 69(3): 359-362.

USDA NASS. 2011. National Statistics for Corn. NASS.

Wan, G. H., W. E. Griffiths, and J. R. Anderson. 1992. Using Panel Data to Estimate Risk Effects in Seemingly Unrelated Production Functions. *Empirical Economics* 17(1): 35-49.

Wright, B., and J. Hewitt 1994. All-Risk Crop Insurance: Lessons from Theory and Practice. In D. Hueth, and W. Furtan, ed. *Economics of Agricultural Crop Insurance: Theory and Evidence*. Boston: Kluwer Academic Publishers, pp. 73-112.

Appendix: Data

In this appendix, we provide a more detailed description of our treatment of the data.

Trials by year and state

The number of trials by year and state is shown in table 5, and the number of observations by GM category in table 6. Summary statistics for the variables included in the analysis are provided in table 3 in the text.

Table 5. Number of Trials by Year and State

Year	Illinois	Indiana	Iowa	Kansas	Minnesota	Missouri	Nebraska	Ohio	South Dakota	Wisconsin	Total
1997	1189	981	3693	642	823	1190	1139	1004	535	2146	13342
1998	1069		3245	668	789	308	1169	955	590	2063	10856
1999	2095		3409	621	993	1223	1149	967	634	2159	13250
2000	1810	1626	3575	555	985	334	1332	853	556	1997	13623
2001	1739	1710	3321	671	859	1168	1087	844	593	1767	13759
2002	1302	1629		505	697	1201	1010	844	481	1765	9434
2003	1630	1155		466	735	1389	996	888	522	1797	9578
2004	2005	1341		672	931	1468	1149	1010	731	1818	11125
2005	1925	1471	2214	679	836	1479	1043	941	494	1803	12885
2006	1816	1196	2607	702	1190	1825	1023	838	640	1682	13519
2007	1778	1160	2810	932	1296	1529	1352	1215	588	2205	14865
2008	2020	1470	2587	1029	1039	1585	1201	1053	472	1779	14235
2009	1565	1241	2397	1028	940	1589	1185	1435	420	1669	13469
Total	21943	14980	29858	9170	12113	16288	14835	12847	7256	24650	163940

Table 6. Number of Trials by Year and GM Category

Year	Total conventional	CB only	RW only	Ht only	CBHt	CBRW	RWHt	CBRWHt	Total GM	Total number of trials
1997	12906	408		20	8				436	13342
1998	9683	1048		78	53				1179	10862
1999	8694	3589		705	269				4563	13257
2000	9730	3289		445	151				3885	13615
2001	9880	2910		671	301				3882	13762
2002	5579	2755		533	567				3855	9434
2003	3653	4319	47	497	1047		8	7	5925	9578
2004	3133	5242	219	672	1713	25	77	44	7992	11125
2005	3633	4979	122	925	2678	194	107	247	9252	12885
2006	1955	3031	149	1123	4466	462	421	1912	11564	13519
2007	589	1517	24	916	4387	433	501	6498	14276	14865
2008	446	666	9	608	1881	200	425	9999	13788	14234
2009	476	246	2	378	1544	58	114	10645	12987	13463
Total	70357	33999	572	7571	19065	1372	1653	29352	93584	163941

Missing data

We have relied on the cooperation of the various extension services to obtain copies of those reports which are not available online, and some records are not complete.

- Iowa has the longest history of testing but records are incomplete. Records are complete from 2005. Professor Joe Lauer of UW Madison was able to provide us with data for individual locations for 1997-2001. The years 2002-2004 are lost. Even though we only have ten years of Iowa data the number of trials is substantial.
- Cultivation type and rotation were not reported by Ohio for 1998-2002 but the locations and agronomic practices for other years are consistent so that we have assumed that the same cultivation methods and rotation decisions were made.
- Indiana in some years reports only regional average yields, so we have omitted those years and those locations where individual site results are not reported. This means that we have no entries for 1998-1999, and limited entries for 1997.
- The University of Missouri is missing reports for 1998 and 2000, but some of the 1998 and 2000 results are reported in the following years' reports and we have included those results.

Dependent variable

Grain yields are reported as bushels per acre of shelled grain (56 lb/bu) adjusted to a moisture content of 15.5%. As expected, the average annual yield for each state for these trials is consistently above the average annual corn yield for each state published by the National Agricultural Statistics Service of the USDA (see table in part E of the supporting material online).

Agronomic variables

Early or late

Most states conduct early and late maturity trials, but in some cases the distinction was not made until the late 1990s or early 2000s. Some states still do not make a distinction. If there is not a specific statement that the trial is early season we have assumed that it is late. Nebraska reports on mid trials in some years but we have classified these as late. A dummy variable is used to indicate an early trial.

Irrigated or dryland

Missouri, Nebraska, Kansas, and Wisconsin conduct irrigated trials, and a dummy variable is included to indicate whether a trial is irrigated.

Minimum or no till compared with conventional tillage

Type of cultivation is reported in some detail and it has been impossible to account for all of the variations. A dummy variable has been used to indicate minimum or no till preparation, but only where this is explicitly stated. The default variable is conventional and everything other type of cultivation is included in this category.

Soil type

Seven soil types are identified by dummy variables, with silt loam as the default soil. The only state that does not report soil type is Minnesota and we have used the coordinates for each trial location and the Soil Web Survey of the USDA Natural Resources Conservation Service (2010) to identify the predominant soil type in that location.

Rotation

Previous crop is also reported for most locations. However, Illinois does not report on rotation, and, in a small number of other locations in other states, the rotation is omitted. As soybean is the usual rotation crop, we have assumed that this is the previous crop where it was missing. Dummy variables have been included for corn, wheat, alfalfa, and other, with soybean as the base case.

Plant density

Generally a seeding rate is reported, although in some states final plant population is given instead. We have used final plant population (in thousands) where possible, but if this was not available we have substituted seeding rate. This is not exactly comparable, but the order of magnitude is in general similar.

Fertilizer

We have nitrogen fertilizer application in lbs/acre for most states. However, Illinois started to report fertilizer application rates only in 2000. Iowa does not report fertilizer rates. We included a zero value for the missing observations. To differentiate between cases where nitrogen use was reported as zero, and the missing observations, we have introduced a dummy variable with a value of 1 indicating "Nitrogen not reported". Although some states do report phosphorus and potassium application, others do not, and we have not included these fertilizers in our analysis.

Pesticides and herbicides

It would have been useful to include pesticide and herbicide application rates. However the variety of different combinations that are possible and that have been used over the past 20 years is immense. We have assumed that the trials are conducted so as to eliminate pest and weed infestations.

Climatic variables - rainfall and average maximum and minimum temperatures

In most cases the trial reports include rainfall for the growing months. If not, for example for Ohio and Iowa, there is generally a very good network of weather stations and it has been possible to extract monthly rainfall from their databases (Iowa

Environmental Mesonet 2009; OARDC 2009). For those states which do not report specific rainfall figures (Nebraska includes column charts, and Minnesota does not report rainfall) we have used the database provided by the PRISM Climate Group at the University of Oregon (PRISM Climate Group Oregon State University 2009). This allows monthly rainfall, minimum and maximum temperatures to be extracted based on latitude and longitude coordinates. Some universities have reported rainfall May-September, others April-August and others April-September. We have filled the gaps for the months April-September from the PRISM database. As temperature is likely to be less local than rainfall, we have extracted minimum and maximum monthly temperatures April-September from the PRISM database.

Other variables

Location where trial conducted

We have details of the location where the trial was conducted. The locations are not necessarily exactly correlated with the included site characteristics. The trials may not be at exactly the same site each year, or may be at different farms or sites in the immediate area. At some locations trials are held on more than one soil type. The weather data is by location, not by CRD. Therefore weather is not exactly correlated with the CRD-year interaction term included in the models.

Interaction term for year by Crop Reporting District (CRD)

It is likely that there are some factors that are variable by year and by location. In particular, we do not include variables related to pest pressure or chemical use, because it was too difficult to obtain consistent information across states. The CRD by year interaction terms are therefore included to account for different chemical usage practices and different degrees of pest infestation. As mentioned in f(i), weather is reported by location, not CRD,

GM traits and stacking of traits

We have details of the GM traits associated with each hybrid. We have identified the presence of these traits using dummy variables, and have also created dummy variables to indicate the combinations of traits where traits are stacked. The base case is no GM traits. The number of trials by year and by category of GM traits for the whole dataset can be found in table 3 and figure 1 in the text.

Hybrid identifiers

The trial reports provide the name of the company submitting the hybrid for trial, the name of the hybrid, and, since the introduction of genetically modified hybrids, the GM traits associated with each hybrid. Since some quite different hybrids have the same number, we have identified each separate hybrid by combining the name of the submitting company and the name of the hybrid. It is this variable that we have used to create dummy variables for our cross section. Where the hybrid number is the same, and the submitting company has changed, but is known to be affiliated with the previous submitting company, we have considered the hybrids to be identical. In some cases a hybrid will have the same name, but a different submitting company in consecutive years. For example, Keltgen, Lynks and Mycogen all submitted a hybrid with the same name in different years in the mid 1990s. Mycogen acquired Keltgen and Lynks in the early to mid 1990s, so we have assumed that these hybrids are in fact the same, and have renamed the hybrid identifier accordingly. Kruger Seed Company has at times submitted seed under the company names Kruger, KSC/Challenger, Circle and Desoy. We have based our decision on the ownership groups shown in table A1. This table was collated from numerous sources, including company reports, company websites, media releases and newspaper articles. It is accurate, to the best of our knowledge, as at December 2011.

Table 7. Ownership of United States Seed Breeders and Distributors

Monsanto		DuPont	Syngenta	AgReliant	Dow
Asgrow	Heritage	Pioneer	AgriPro	AgriGold	AgriGene
Campbell	High Cycle	Curry	Blaney	Callahan	Cargill
CFS	Hubner	AgVenture	CIBA	Dahlco	Dairyland
Challenger	ICORN	Adler	Elite	Great Lakes	Golden Acres
Channel	Jung	Frontier	Funks	Herried	Grand Valley
Cheesman	Kruger	McKillip	Garrison	Horizon	Growers
Circle	Lewis	Select Seed	Garst	J M Schultz	Jacques
Crows	Linco	Spangler	Golden Harvest	LG Seeds	Keltgen
DeKalb	Midwest	Doeblers	Gutwein	McAllister	Lynks
Desoy	NC +	Hoegemeyer	HyPerformer	Noble Bear	McCurdy
Didion	REA	NuTech	ICI	Pride	Mycogen
Diener	Sieben		NK	Producers	ORO
Fielders Choice	Specialty	Seed Consultants	Novartis	Shissler	Pfister
Fontanelle	Stewart	Terral	Payco	Voris	Prairie Brand
Gold Country	Stone	**Alliances**	PSA	Wensman	Renze
Grow Direct	Trelay	Beck	Stauffer		Schillinger
Hawkeye	Trisler	Wilken	Sturdy Grow		Shur Grow
Heartland	Wilson	Burrus	Super Crost		Sigco
					Taylor Evans
					Triumph
					Vineyard

Table 8. Full Results (but not including the year by CRD interaction term)

VARIABLES	(1) varianceFEresid residFE2sq	(2) skewnessFEresid residFE2cub	(3) varianceHTresid residHTsq	(4) skewnessHTresid residHTcub
GM traits (Conventional as base)				
Corn borer resistance (CB)	86.44***	-3,225***	82.86***	-2,982***
	(14.72)	(1,021)	(14.64)	(1,018)
Rootworm resistance (RW)	-17.74	1,648	-16.46	1,472
	(71.82)	(5,727)	(71.49)	(5,710)
Herbicide tolerance (Ht)	41.37*	-1,426	44.17*	-1,682
	(24.73)	(1,823)	(24.61)	(1,818)
CB and Ht	141.0***	-6,256***	139.5***	-6,442***
	(21.50)	(1,731)	(21.42)	(1,726)
CB and RW	289.1***	-9,006***	289.2***	-9,389***
	(49.04)	(3,407)	(48.78)	(3,398)
RW and Ht	181.5***	-4,572	177.3***	-5,418
	(50.38)	(3,651)	(50.13)	(3,640)
CB, RW and Ht	97.95***	-5,342**	94.21***	-5,760**
	(25.85)	(2,244)	(25.79)	(2,237)
Plant density	-1.431	-1,076***	-0.0708	-1,175***
	(2.098)	(257.7)	(2.101)	(256.9)
No min till	43.96***	-1,481	37.78**	-1,304
	(15.94)	(1,958)	(15.96)	(1,952)
Irrigated	-92.82***	10,972***	-95.11***	11,454***
	(20.55)	(2,523)	(20.58)	(2,515)
Early	-56.32***	1,798	-58.54***	1,512
	(9.469)	(1,093)	(9.475)	(1,090)
Previous crop: Corn	169.4***	-11,288***	166.2***	-11,638***
	(14.32)	(1,755)	(14.33)	(1,750)
Previous crop: Wheat	199.2***	-11,310***	201.5***	-10,985***
	(20.15)	(2,473)	(20.17)	(2,466)
Previous crop: Alfalfa	108.6***	-1,883	95.81***	-772.9
	(27.29)	(3,348)	(27.32)	(3,338)
Previous crop: Other	347.4***	-24,428***	337.7***	-23,819***
	(29.21)	(3,586)	(29.25)	(3,575)
Nitrogen in lbs/ac	-0.603***	11.34	-0.541***	9.472
	(0.121)	(14.86)	(0.121)	(14.82)
Soil type: Clay	204.9***	-2,333	212.8***	-2,414
	(57.05)	(7,007)	(57.12)	(6,987)
Soil type: Silty clay loam	-97.20***	5,465***	-94.94***	5,393***
	(11.35)	(1,392)	(11.36)	(1,388)
Soil type: Clay loam	-133.3***	2,930	-141.1***	3,113*
	(15.31)	(1,878)	(15.32)	(1,873)
Soil type: Loam	-42.10**	-1,472	-33.35*	-1,578
	(18.80)	(2,308)	(18.82)	(2,301)
Soil type: Sandy loam	364.2***	-17,917***	383.4***	-19,377***
	(18.66)	(2,292)	(18.69)	(2,285)
Soil type: Sand	657.9***	-13,935**	695.4***	-17,436***
	(55.23)	(6,782)	(55.30)	(6,762)
Rainfall				
April	-15.51***	333.7	-15.76***	435.3
	(4.302)	(528.2)	(4.307)	(526.7)
May	-6.422**	1,042***	-6.399**	1,070***
	(2.959)	(363.4)	(2.963)	(362.3)
June	16.19***	373.4	16.95***	433.2
	(2.472)	(303.5)	(2.475)	(302.6)
July	-13.45***	-1,092***	-13.84***	-1,097***
	(2.772)	(340.3)	(2.775)	(339.3)
August	2.635	11.94	3.337	-0.759
	(2.659)	(326.4)	(2.662)	(325.4)
September	15.79***	-640.4*	14.97***	-642.0*

	(3.119)	(383.0)	(3.123)	(381.9)
Mean minimum monthly temperature				
April	-9.125***	-384.7	-9.859***	-376.9
	(2.266)	(278.3)	(2.269)	(277.5)
May	32.88***	-2,885***	34.13***	-2,827***
	(6.413)	(787.3)	(6.420)	(785.0)
June	-34.69***	345.7	-32.90***	198.9
	(6.938)	(852.0)	(6.946)	(849.6)
July	-7.938	1,846**	-11.08	1,842**
	(7.640)	(938.3)	(7.650)	(935.6)
August	-1.763	475.5	-2.730	583.4
	(6.834)	(839.1)	(6.842)	(836.7)
September	1.466	1,067**	1.964	1,119**
	(3.642)	(447.2)	(3.646)	(445.9)
Mean maximum monthly temperature				
April	18.31***	1,687***	19.60***	1,686***
	(4.288)	(526.6)	(4.293)	(525.1)
May	-18.48***	2,865***	-23.03***	2,978***
	(5.525)	(678.1)	(5.531)	(676.1)
June	40.75***	-1,707**	42.13***	-1,666**
	(6.153)	(755.4)	(6.160)	(753.2)
July	6.353*	-575.1	6.836*	-541.7
	(3.500)	(429.9)	(3.505)	(428.6)
August	-21.34***	-4,419***	-21.58***	-4,599***
	(6.164)	(756.6)	(6.171)	(754.5)
September	3.414	938.2	6.259	864.5
	(5.631)	(691.0)	(5.637)	(689.0)
Constant	-1,164**	178,162***	-1,437***	194,387***
	(538.1)	(66,016)	(538.7)	(65,825)
Observations	147,790	147,790	147,790	147,790
Number of hybrids	8,423	8,423	8,423	8,423

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1