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Valuing New Random Genetically Modified (GM) Traits in Corn

Sumadhur Shakya, William W. Wilson, and Bruce Dahl

Numerous genetically modified (GM) traits are currently under development. Those currently being developed for corn include traits for drought tolerance, cold tolerance, and nitrogen use efficiency, among others. The value of these traits is random and sporadic, creating challenges in assessing its *ex ante* value. This study estimates the *ex ante* value of a GM trait in corn with random characteristics. A real option model is developed to capture risks and returns associated with the traits, and estimates are derived for drought tolerant corn. Base case results indicate a slight chance that the option value would be out-of-the-money during the discovery phase. In all other phases, the expected value is in-the-money. The results are highly sensitive with respect to trait efficiency and regarding assumptions of randomness in some of the other important variables, particularly trait values.

Key words: real options, risk premium, stochastic efficiency, trait valuation

Introduction

Genetically modified (GM) crops have had a dramatic impact on agriculture worldwide. Corn has benefited immensely from the introduction of GM traits, and many new traits are under development, including drought and cold tolerance and nitrogen-use efficiency (McMahon, 2011; Birger, 2011a,b). While earlier GM traits had relatively ubiquitous applications, the value of these new traits is less clear because their usefulness depends on sporadic environmental conditions. For agbiotechnology firms, determining the value of future prospective traits is an important managerial decision. There is a high degree of uncertainty regarding many of the factors that determine trait valuation, including efficacy, regulatory approval, commercial acceptance, competing traits, and prices that can be charged for a trait. The high uncertainty of trait valuation means that the *ex ante* values of traits are also random.

This study estimates the *ex ante* value of GM corn traits with random valuations, in this case drought-tolerant (DT) corn. Trait development is considered research and development (R&D) and is interpreted as a real option. While there are many types of real options, here R&D is interpreted as a compound-call option. Given the risks and returns across traits, this interpretation is appropriate for determining the *ex ante* value for these GM traits.

The analysis estimates distributions for farm budgets with and without the trait, the value of which depends on drought probability and trait efficiency. We then determine the grower's value by estimating risk premiums for simulated budgets using stochastic efficiency with respect to a function (SERF). This grower's value is the basis for trait prices in the option model. A real-option

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model is used to estimate the trait's stochastic value at each stage of development. The study builds on earlier research using real options to evaluate R&D (e.g., Kolbe, Morris, and Teisberg, 1991; Luehrman, 1997; Lee and Paxson, 2001; Jensen and Warren, 2001; Seppä and Laamanen, 2001) and applications of real options to value post-development costs and benefits for GM traits in crops (e.g., Furtan, Gray, and Holzman, 2003; Carter, Berwald, and Loyns, 2005). This study contributes to the literature by using real options to value *ex ante*, firm-level management decisions, with random variables in a stochastic binomial specification.

Background

Developing and marketing GM traits can be costly and time-intensive. Discovery, proof of concept, early and advanced product development, and regulatory phases can take ten to fifteen years to complete, and revenue from successful development can only be realized after regulatory approval. Estimating development costs is difficult because these are ultimately firm-level activities and information is generally not published. Goodman (2004) estimated that developing a GM trait costs $60 million and that the regulatory approval process can cost $6–15 million (Kalaitzandonakes, Alston, and Bradford, 2006). A recent estimate of total cost to develop a GM trait in the United States, including costs related to regulatory approvals, is about $136 million (McDougall, 2011). Additionally, substantial uncertainty exists throughout the development and commercialization process regarding costs, time to develop, and trait efficiency and success (Monsanto, 2004).

Until 2009, the dominant GM traits in corn were Roundup Ready (RR) and *Bacillus thuringiensis* (Bt). Along with some other traits, these could be stacked in multiples of three or four genetic modifications in single varieties. Each biotechnology company invested substantially to develop a multitude of traits for corn and other crops, as summarized by McMahon (2011) for investment by company and by Birger (2011a,b) in reference to nitrogen-use efficiency. In addition to drought tolerance, other traits with random values that are being developed include cold tolerance and nitrogen use-efficiency.

The characteristics of traits under development illustrate a number of important points (Wilson and Dahl, 2010a,b). First, a large number of traits are anticipated in the next ten or more years, including twenty-one new GM traits for corn. Second, some of these traits are producer traits, some are processor traits, and others are consumer traits. Although producer traits dominated early commercialization, the trait-development focus expanded to consumer and processor traits as the market matured. Third, a number of traits are being developed jointly, such as Monsanto's SmartStax, developed in collaboration with Dow AgroSciences, and Monsanto's first drought-tolerant GM traits, the result of collaboration with BASF.

Additionally, several forms of herbicide tolerant and DT traits are currently planned. Monsanto will potentially be the first company with a DT product on the market, followed by Syngenta and later by Pioneer/DuPont (McMahon, 2011). An additional trait, nitrogen-use efficiency, will be commercialized first by Monsanto, with Pioneer and Syngenta following. Many of these traits will be released as stacked traits, similar to SmartStax, which was approved for release in 2010 and had eight traits stacked in one variety.

Trait efficiency is a measure of how much the technology increases some attribute of the underlying crop relative to incumbent technologies. It provides value for the trait and ultimately influences its price and commercial success. Limited information exists about trait efficiency until the trait is released because firms are hesitant to release this information to competitors. Firms are constantly choosing among possible events, each of which may have slightly different trait efficiencies; until the event is chosen, any information is highly preliminary and proprietary. Trait efficiency is important analytically because it impacts trait value, which is concurrent with trait-development decisions. Presumably, these calculations are made simultaneously during the development process.

Drought Tolerance and Trait Efficiency

Although the concept of drought tolerance is not novel, at least three companies are currently using genetic engineering—a novel technique—to improve drought tolerance in crops.[1] Drought tolerance allows corn to be produced in geographies with less rainfall and with greater risk of drought. The goal of these modifications is to reduce crop-yield losses during drought (Brasher, 2011), given that approximately 40% of crop losses in North America are due to suboptimal moisture (Abbott, 2011).

Previous studies inferred information about the efficiency of drought tolerance traits in corn. Edmeades (2006); Edmeades et al. (2006); Edmeades (2008) described the genetic technology for drought tolerance, its effect, and likely distributions. Edmeades et al. (2006) suggested that it is possible to eliminate 25% of drought-related yield losses through genetic improvement, 25% through water-conserving agronomic practices, and the other 50% through irrigation. He suggested that yields could potentially be improved by 8–22% under the drought stress that reduces yields by 50% but did not distinguish between GM technology and market-assisted breeding. DT corn, including Pioneer's AQUAmax and Syngenta's Artesian lines, is also being developed using non-GM technology. There have been some concerns that GM technology may not be keeping pace with conventional breeding, which "is producing drought tolerance two to three times faster than genetic engineering" (Union of Concerned Scientists, 2012). In either case, trait-efficiency measures for drought tolerance vary.

Tests by Monsanto (2009a) indicated that first-generation DT corn varieties had yield advantages of 7–13% and second-generation varieties had yield advantages of 9–15% compared to nonmodified corn; additionally, there was a 9–10% yield advantage reported for low-drought seasons and 15% advantage for high-drought seasons. These findings suggest that yield advantages for drought-stress varieties improve as drought stress increases. The interpretation of yield increases from genetic improvement for drought tolerance is as rightward rotation of the corn-yield distribution relative to current technologies. These distributions are illustrated in figure 1 by using data for trait efficiencies of 0.12 and 0.20 as used in this study.

Monsanto developed DT corn as a GM trait. The Monsanto event (MON 87460) has a bacterium gene that allows the plant to survive on less water during flowering (Brasher, 2011). This trait was under development for a long time and was deregulated in late 2011 (Abbott, 2011), leading the way to begin farm trials in 2012 (Gillam, 2011). Early results for the 2012 farm trials are anecdotal but suggest efficiency gains. The 2012 field trials indicated that "corn farmers will lose one-quarter less of their crop than they did during the 1988 drought" (Mertens, 2012). Results in Texas and Kansas revealed up to a six-bushel advantage over competitor hybrids (Monsanto, 2012), and another observation in Indiana suggested "a significantly higher yield, by 30–50 bushels" (Leber, 2012).

Real Options as a Technique for Valuing GM Traits

An extensive literature on real options exists (see Schwartz and Trigeorgis, 2001, who describe the evolution of this method and its role in valuing R&D). Important features of the problem are that uncertainties are resolved through time and managers have options to exercise throughout the development process. R&D investments are made through time, providing the option to continue, wait, or abandon. R&D investing is a call option and can be valued as a real option because it involves future opportunities, uncertainty, and options. Kolbe, Morris, and Teisberg (1991) and Luehrman (1997) explain why R&D can be modeled as real options and Lee and Paxson (2001), Jensen and Warren (2001), and Seppä and Laamanen (2001) offer multiple applications of this choice. R&D

[1] Breeders have focused on drought for many years and have probably increased drought tolerance of corn (Campos et al., 2004), though it may not have been an explicit objective. Drought tolerance has also been a focus for trait development in other crops, including rice (Reyes, 2009) and wheat. Genes activated by drought that would avoid any yield penalty under normal conditions are currently being identified (an efficiency gain for a drought-resistant gene is realized when a drought occurs) to avoid any yield penalty with normal conditions. Jacqui (2008) has suggested that "drought tolerant crops look to be one of the most promising upcoming biotech traits in pipeline, providing ability to produce 'more crop per drop' of water."

for new GM traits lends itself well to using the real-options framework for valuation because the development process is staged and each stage has measurable risks and outcomes.

The option value may be either in-the-money when expected cash flows exceed development costs or out-of-the-money otherwise. This paper uses a stochastic binomial option model to represent R&D of GM traits as a compound-call option. The continue growth option represents the decision to move to the next stage and make further development investments. If the option value were in-the-money, management would make decisions to continue with development. If the option value were out-of-the-money, management would choose to wait before making a further investment. The option to wait for any stage is valued the same as the option to continue the previous stage with an additional timeframe added to it without investing in a subsequent stage. The option to abandon evaluates the salvage value at the current investment stage.

Real options have been used previously to value GM wheat (Flagg, 2008). Carter, Berwald, and Loyns (2005) and Furtan, Gray, and Holzman (2003) analyzed decisions from a public sector perspective and were modeled as irreversible post-development timing options; the values were derived using an adaptation of the Black-Scholes model. These approaches differ from ours in a number of respects. Most importantly, we modeled decisions for private firms during the R&D process, as opposed to a more comprehensive analysis that included public decisions and social costs and benefits. Second, they modeled the problem as a timing decision that was part of a public process. Our approach differs in that it considers real options confronting managers of agbiotechnology companies during the development process. Further, their primary concern was uncertainty in post-product development, as opposed to modeling uncertainties within the R&D process. Our approach views how managers confront R&D investment decisions through time and confront uncertainties and decisions about whether to continue, wait, or abandon at each phase. Finally, in our approach, many parameters are random. Thus, we derived the option value at each phase using stochastic methods.

Valuing Drought Tolerance at the Farm Level

Figure 2 summarizes the two major steps in our methodology. First, we derive estimates of the DT traits at the farm level. Farm budgets are simulated to measure risk and returns with and without the new trait. Stochastic efficiency with respect to a function (SERF) is then used to estimate certainty equivalents with and without the trait, which are used to derive the grower's risk premium for the trait. The risk premium is defined as the value of the certainty equivalent required for a grower to be indifferent between the variety with and without the trait or, alternatively, the value of the grower's preference for one technology over the other. The grower's risk premium for the trait is then used as the basis for pricing new traits and is an input for the option model. Second, we use these results in a real-option model that aggregates the findings from the first step and applies the logic of the real-option methodology to estimate option values for each phase of GM-trait development.

Farm Budgets, Yields, and Trait Efficiency

The analysis quantified growers' risks with and without the trait. We used farm budgets for each USDA-defined crop-reporting region (U.S. Department of Agriculture, Economic Research Service, 2010). The budgets were simulated to estimate net returns and risk per acre. Random variables in the simulated budgets included crop yields; prices; costs for seed, chemicals, and fertilizer; and the probability of drought and coverage. Historical data for yields from current technology, prices, and costs were fitted to distributions by budget region using data from 1996 to 2009 (U.S. Department of Agriculture, Economic Research Service, 2010). These are shown in table 1.

Returns to labor and management (RLM) for current technology were defined as:

$$RLM_i = [(\hat{P}_i \times \hat{Y}_i) - (\hat{S}_i + \hat{F}_i + \hat{C}_i + OC_i + FC_i)], \quad (1)$$

Table 1. Distributions and Characteristics for Grower Budget Analysis, by Region

Item	Region					
	Heartland	Northern Crescent	Northern Great Plains	Prairie Gateway	Eastern Uplands	Southern Seaboard
Yield						
Distribution	Logistic	Beta General	Lognormal	Logistic	Logistic	Logistic
Mean	151.76	127.29	112.33	140.41	113.37	113.57
Std. Dev.	10.23	17.25	14.75	10.23	18.92	14.12
Drought						
Distribution	Beta General	Exponential	Extreme Value	Exponential	Exponential	Exponential
Mean	0.41	0.20	0.32	0.19	0.22	0.19
Std. Dev.	0.41	0.20	0.19	0.19	0.21	0.19
Correlation Yield Drought	−0.84	−0.93	−0.92	−0.83	−0.89	−0.93
Seed						
Distribution	Pareto	Exponential	Exponential	Inverse Gaussian	Exponential	Exponential
Mean	41.04	44.40	36.71	38.54	33.95	39.92
Std. Dev.	22.66	14.26	12.44	12.57	14.32	13.19
Fertilizer						
Distribution	Exponential	Exponential	Inverse Gaussian	Exponential	Inverse Gaussian	Exponential
Mean	69.14	86.54	42.34	51.06	87.71	84.35
Std. Dev.	27.59	38.90	31.25	19.01	47.19	32.41
Chemicals						
Distribution	Extreme Value	Exponential	Extreme Value	Extreme Value	Beta General	Logistic
Mean	27.73	23.68	19.09	25.01	27.29	24.21
Std. Dev.	1.96	2.81	2.10	4.26	3.82	1.63
Price						
Distribution	Extreme Value	Exponential	Exponential	Exponential	Exponential	Exponential
Mean	2.42	2.52	2.33	2.54	2.56	2.81
Std. Dev.	0.67	0.86	0.84	0.84	0.78	1.16

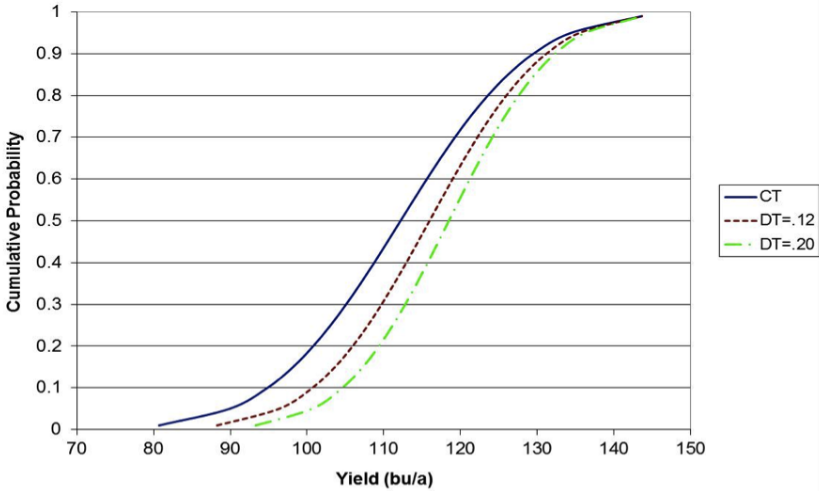

Figure 1. Yield Distributions for Current Technology, Drought Tolerance with Trait Efficiency = 0.12 and 0.20, Northern Great Plains Region

where P is price, Y is yield for current technology, S is seed cost, F is fertilizer cost, C is chemical cost, OC is other operating costs, and FC is fixed costs for region i; variables with ˆ are random and drawn from fitted distributions.

Yields for DT corn were estimated for current technology (without the trait), trait efficiency, and a probability distribution of drought coverage within the region. To accommodate a rightward rotation in yield distributions for drought technologies, yields for DT varieties were modeled assuming:

$$(2) \qquad Yield_{DT} = Yield_{CT} + (MaxYield_{CT} - Yield_{CT}) \times TraitEfficiency \times DroughtCoverage,$$

where CT and DT refer to current technology and drought tolerant, $Yield_{DT}$ is the yield for DT varieties, $MaxYield_{CT}$ is maximum yield, $Yield_{CT}$ is random draw for yield, $TraitEfficiency$ is the trait efficiency for the DT variety, and $DroughtCoverage$ is a random variable that indicates the distribution for the proportion of area covered by drought.

Distributions for drought coverage were derived using data from the National Drought Mitigation Center (2006). We assigned river basins to ERS budget regions based on which basin was predominant within each region.[2] Data for each basin were fitted to derive distributions for the budget region's drought coverage. The fitted distributions are listed in table 1 and are used in the budget simulations. Correlations between yield and drought-coverage levels were estimated by mapping the joint cumulative distributions for yields and drought coverage, assuming that yield losses were due solely to drought. The joint cumulative distributions for yields and drought coverage were defined at percentiles of the distribution from 5–95% such that high yields were associated with low drought coverage and low yields were associated with high drought coverage. Correlations were computed from these joint observations. The distributions for and correlations between yields and drought coverage were used in the budget analysis to simulate yields for CT and DT technologies as well as the likelihood of drought by region. While yield losses can occur due to other environmental differences, it implies that lower CT yields occur when droughts cover a wider area of the budget region and should represent an upper bound for the value of the DT trait.

Trait efficiency for DT corn was inferred from published studies. Specifically, we define a base case value of 0.12 and apply it to the yield difference from the maximum yields for the region (as shown in figure 1). This transformation implies that a DT variety can recover 12% of the yield

[2] River basins are geographic regions defined by the National Drought Mitigation Center (2006).

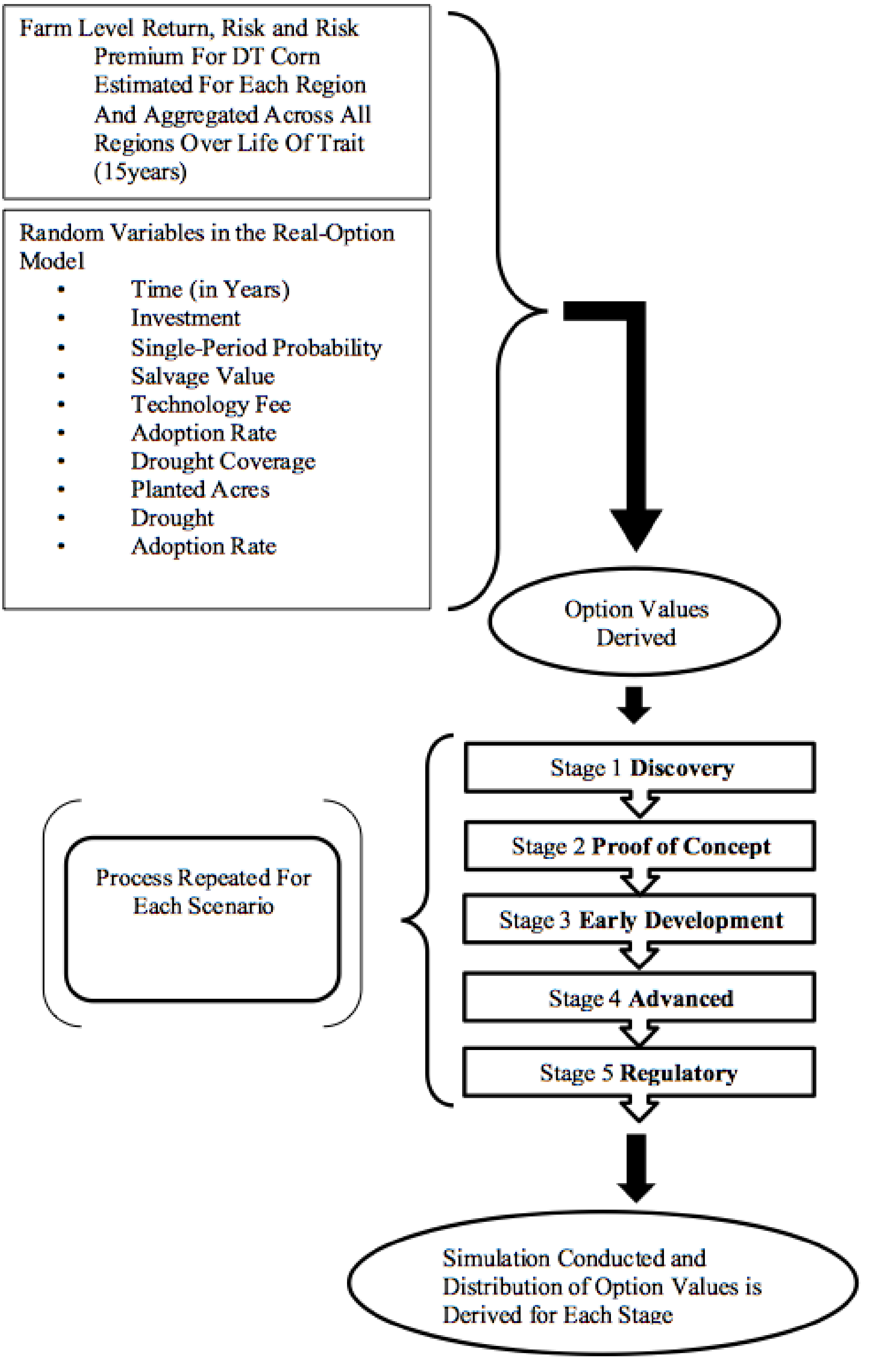

Figure 2. Overview of Simulation Methodology

Table 2. Relationship Between Yield Loss and Drought-Tolerant Yield Advantage by Trait Efficiency (Northern Great Plains)

Conventional Technology	GM Drought-Tolerance Technology	
	Trait Efficiency =0.12	Trait Efficiency = 0.20
Yield Loss	*Yield Advantage of DT*	
Mean (112 bu/a)	3%	5%
-25% (84 bu/a)	6%	11%
-50% (56 bu/a)	10%	16%

Notes: Assumes that max yield is 138 bu/a and mean=112 bu/a.

loss attributable to drought, which is similar to values suggested by Edmeades (2008). Monsanto (2009a) indicated a yield advantage of about 6% for a 25% yield loss and a 10% yield advantage for a 50% yield loss in the Northern Great Plains region (table 2). In other regions, the yield advantage increased slightly, so DT yields were up to 12% higher for a 50% yield loss and 8–9% higher for a 25% yield loss with a trait efficiency of 0.12. We conducted sensitivities on these values.

Simulation Procedures, SERF, and Risk Premiums

Budgets were simulated with and without the DT trait for each region using Monte Carlo procedures in risk (Palisade Corporation, 2007). The model was iterated 10,000 times; at that time, stopping criteria indicated that additional iterations would not improve results. Random variables included yield, drought coverage, price, and costs for fertilizer, seed, and chemicals. Correlations among random variables were included where significant.

Stochastic efficiency with respect to a function (SERF) was used to estimate the certainty equivalent that growers would place on a risky alternative relative to a no-risk investment (Hardaker et al., 2004). Certainty equivalents were estimated from the simulated distributions for returns to labor and management for the corn budgets with and without the DT trait by region for growers' risk attitudes that range from risk neutral (relative risk averse coefficient (RRAC= 0) to highly risk averse (RRAC= 4). The risk premiums were used as the basis for trait prices in each region.

Real-Option Methodology

Real Options

R&D for GM trait development is modeled as a compound option, consisting of the options to continue, wait, or abandon. The option value is modeled as a stochastic binomial model using discrete event simulation where the variables change at discrete points in time (in contrast to a continuous system where state variables change continuously over time). Several methodologies can be used for quantifying real-option values, including transformations conforming to the Black-Scholes models as well as others using more stylized binomial pricing models and/or Monte Carlo simulation techniques. We used Monte Carlo simulation because there were numerous distributions, many of which were nonnormal. The binomial model of real-option values was specified as an option tree encompassing each phase of GM trait development and was simulated over a fifteen-year period. Phases of the R&D and commercialization process were defined along with estimates about the probability for success and the costs for each phase (Seppä and Laamanen, 2001).

The model specifies a binomial option tree with multiple steps. The option price is solved at the initial node, which is done by repeatedly applying the principles described above (Hull, 2005). The length of time is replaced with Δt years to account for multiple steps in the binomial pricing method:

(3) $$f = e^{-r\Delta t}[pf_u + (1-p)f_d;$$

(4) $$p = \frac{e^{r\Delta t} - d}{u - d};$$

where f is the payoff corresponding to upper node u and lower node d, p and $(1-p)$ are the probabilities for reaching the upper and lower nodes, and r is the risk-free rate of interest. Equation (3) is used again in following sequence of equations to represent a multi-step binomial model:

(5) $$f = e^{-r\Delta t}[pf_{uu} + (1-p)f_{ud};$$

(6) $$f = e^{-r\Delta t}[pf_{ud} + (1-p)f_{dd};$$

(7) $$f = e^{-r\Delta t}[pf_u + (1-p)f_d;$$

Equation (5) represents the payoff from the option that can reach the upper node and then lower node through consecutive choices. Equation (6) represents the payoff from reaching the upper node and then the lower node, or reaching the lower nodes twice. Substituting from these equations results in:

(8) $$f = e^{-2r\Delta t}[p^2 f_{uu} + 2p(1-p)f_{ud} + (1-p)^2 f_{dd}].$$

The variables p^2, $2p(1-p)$, and $(1-p)^2$ are the probabilities that the upper, middle, and lower nodes will be reached. The option value is equal to its expected payoff and discounted using the risk-free interest rate (Hull, 2005).

The model is an extension of Jagle (1999), who developed a real-option model for the new product development case. First, the net present value of future expected returns (FER) for the agbiotechnology company is calculated from technology fees (TF), planted acres (PA), and the projected adoption rate (PAR) and is derived over fifteen years after commercialization of the trait is calculated:

(9) $$\sum_{i=1}^{n} FER_i = TF_i \times PA_i \times PAR_i \times (1/(1+I)_i^T),$$

where i refers to the year after commercialization, TF_i is the technology fee charged for year i (in \$/acre equivalent), PA_i is the planted acres for year i, PAR_i is the projected adoption rate for year i, I is the weight-adjusted cost of capital (WACC = 10%), and T_i is the time elapsed after the trait is commercialized for year i. The summation of FER for years 0 to 15 after commercialization is then used to calculate nodal values of the binomial option tree using backward induction. The development time and investment cost are treated as random in the binomial option tree. Each phase has a probability that the GM trait would successfully proceed to the next phase. The cumulative probabilities are from Monsanto (2008) and are converted into single-period probabilities and then treated as risk-neutral probabilities to derive the option value at each node (e.g., development phase). The risk-neural probability for any node is solved as:

(10) $$P = \frac{((1+r)^t) \times -S_-}{(S_+ - S_-)}$$

where P is the risk neutral probability, r is the risk-free interest rate, t is the time in the development phase, S is the current value of the project, and S_+ and S_- are the present cash-flow value at the end of the phase in the case of an upward movement and in the case of a downward movement. Valuations were derived for individual regions, aggregated to comprise the U.S. market value, and then used to evaluate the logic of the option model.

Table 3. Trait Development Assumptions in Real-Option Model Parameters and Distributions

	Distribution Type	Phase of Development				
		Discovery	Proof of Concept	Early Development	Advanced Development	Regulatory Submission
Time (Years)	Uniform	(2, 4)	(1, 2)	(1, 2)	(1, 2)	(1, 3)
Investment ($million)	Uniform	(2, 5)	(5, 10)	(10, 15)	(15, 30)	(20, 40)
Cumulative Probability	Discrete	0.05	0.25	0.50	0.75	0.90
Single Period Probability	Discrete	0.20	0.50	0.67	0.83	0.90

Notes: Monsanto (2008) and Flagg (2008).

Table 4. Risk Premiums for Different Regions at Different Measures of Trait Efficiency, $/acre

Trait Efficiency	Region					
	Heartland	Northern Crescent	Northern Great Plains	Prairie Gateway	Eastern Uplands	Southern Seaboard
0.20	0.00	3.04	10.66	11.56	0.35	3.24
0.12	0.00	1.82	6.39	6.94	0.21	3.43
0.06	0.00	0.91	3.20	3.47	0.11	1.74

Assumptions

A series of assumptions was made to accommodate the analysis. Each is described; in some cases these assumptions are relaxed in the sensitivities. Trait prices, or technology fees (TF), are assumed to be a proportion (γ) of the trait's value to the grower (GTV) and are defined as $TF = \gamma GTV$. In the base case, we assume $\gamma = 0.3$, although this equation is a simplification of a broader, more complicated problem for GM pricing.[3] Typically, agbiotechnology companies assume and price traits such that the price captures 50% of the trait's value to growers (e.g., $\gamma = 0.5$).[4] Monsanto has since indicated that it will reduce the prices for its most expensive crop seeds by as much as 75% in a bid to combat market-share gains by DuPont (Kaskey, 2010). However, Monsanto recently indicated a change in strategy: in the future, the company will seek to capture 30% of the trait's value to the grower (Monsanto, 2010).

Trait prices (technology fees) were based on the trait's value to growers (GTV) and estimated as the risk premiums derived in the SERF analysis. In our base case, we assumed that the GTV was equivalent to the risk premium for a grower with a relative risk aversion of 2. Risk aversion was relaxed in sensitivity because the distribution of growers across risk attitudes was not known. In this sensitivity, we derived a triangular distribution for each region's GTV where the risk premium for RRAC= 2, RRAC= 3, and RRAC= 4 were defined as the minimum, most likely, and maximum values for GTV, respectively.

Acres planted were defined for each USDA crop-budget region. We used the percentage of acres planted to each region as a point of departure (U.S. Department of Agriculture, National Agricultural Statistics Service, 2010). We adjusted the aggregate planted acres to 89 million, which had been used as the total expected planted acreage in the United States.[5] Planted acreage is relaxed in sensitivity. The values used in each region were derived by adjusting them for the fact that there would be no additional acres planted in the Heartland region (assuming this region was already planted as much

[3] This research focuses on valuing a single trait and the prices of that single trait. This is much more complicated for stacked traits. See Gillam (2011) and Shi, Chavas, and Stiegert (2010), who explore pricing stacked traits, and Magnier, Kalaitzandonakes, and Miller (2010).

[4] Traditionally, the technology fee is defined as one-half the value of the risk premium as defined above (i.e., half of negative exponential utility weighted risk premiums). This is in line with analyst Mark Gulley's comments on Monsanto: "They are in essence splitting the value of extra yield 50–50" (Kaskey, 2009).

[5] This value had been used in the period 2009–2011 (e.g., ProExporter). Since that time, the expected acreage planted to corn has increased (ProExporter, 2013).

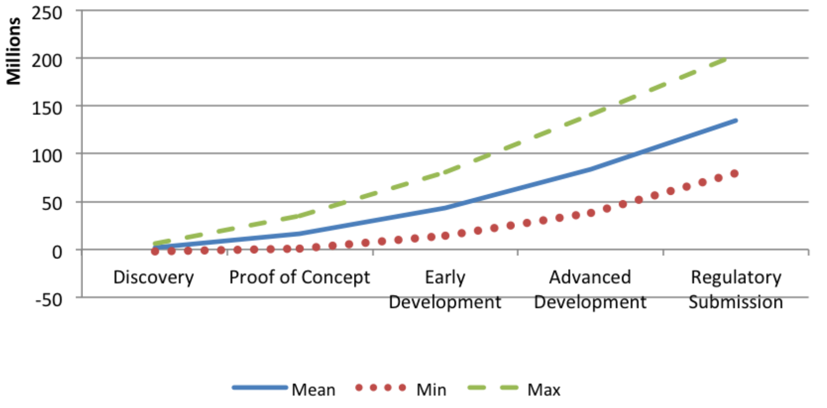

Figure 3. Option Values of 'Drought Tolerance' in Corn Across Stages of Development (RRAC= 2, Trait Efficiency= 0.12, and $ in Millions)

as possible). Hence, the increase in acres (only a slight increase in planted acres aggregated across USDA regions) was allocated across the other regions.

The adoption rate was specified as a triangular distribution, the values of which were subjectively determined to reflect data on adoption rates for GM traits (James, 2008) and industry trends. Specifically, penetration increases and reaches a peak in year 7 after introduction, at 70% of the targeted area, and declines thereafter. Adoption of drought tolerance would be insignificant unless there were consecutive years of drought. To incorporate this situation in the model, the projected adoption rate is correlated with drought occurrence for the previous year. In the case of drought during the previous year, the random draw of adoption rate would tend towards the maximum, otherwise toward the lower half of the distribution. The probability of drought occurrence is modeled as drought coverage area (random) derived from the fitted distributions for drought coverage from the National Drought Mitigation Center (2006) for fifteen simulated years after seed commercialization for the respective regions.

The salvage value represents the value a company may achieve by abandoning the project at any stage of development or by licensing it to a competitor. Because these values are unknown, they are evaluated in the simplest (first-option tree) scenario, in which salvage values are all the bottom nodes. Duration and development cost are each random variables and are taken from previous, publicly accessible reports (Monsanto, 2008, 2009b; Edmeades, 2008). The length of each phase, along with development cost and success probability, are defined and shown in table 3.

Results

Base-case results are shown first. Then, results from the sensitivities on trait efficiency, trait pricing, and more variables are treated as random.

Base Case

The empirical risk premiums are measured as the difference in certainty equivalents relative to corn without drought tolerance. Results for moderately risk-averse growers (RRAC= 2) are shown in table 4. For a trait efficiency of 0.12, the value of DT ranges from 0 in the Heartland to \$6–7/acre in the Prairie Gateway and Northern Great Plains. DT corn would have the greatest value in the Prairie Gateway and the Northern Great Plains, approximately \$6.94 and \$6.39, for our base-case trait efficiency. For obvious reasons, these regions are being targeted for this corn trait. For trait efficiency equal to 0.20, the risk premium ranges upwards to \$12/acre. This increase suggests why it is in the agbiotechnology companies' best interest to select events with the greatest trait efficiency.

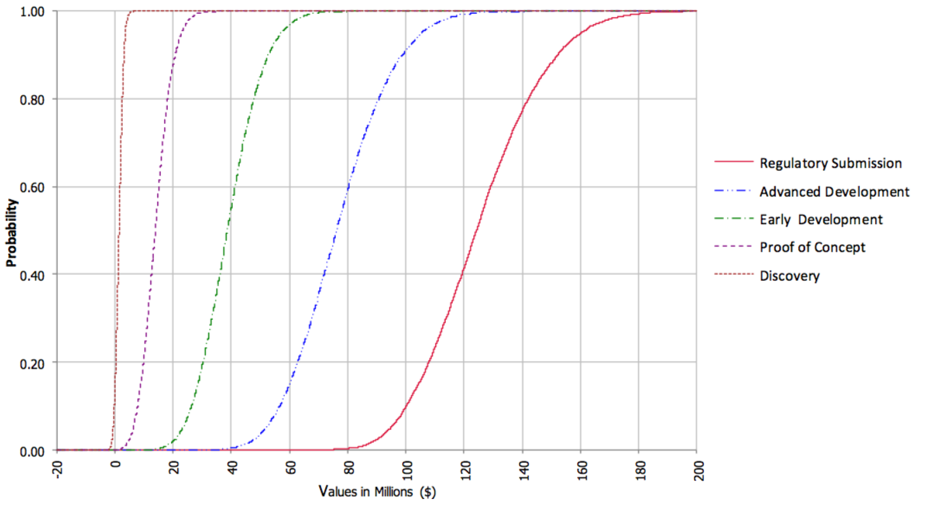

Figure 4. Cumulative Distribution for Option Values of Drought Tolerance across Stages of Development in Corn at a Trait Efficiency$= 0.12$ **($ Millions)**

Decreasing the trait efficiency to 0.06 lowers the risk premium to $3.20–$3.47/acre in the selected regions. For other regions, the value of the trait diminishes substantially.

The option model is first simulated with base-case assumptions and presuming a trait efficiency of 0.12 as defined earlier. Figures 3 and 4 and table 5 (center panel) summarize the base-case results. The results indicate that the mean option value increases with the more advanced development stages. During the discovery phase, there is a chance (probability$= 0.09$) that the option value is negative. Thereafter, the value is in-the-money for each development phase.

The cumulative distributions (figure 4) of the option values at different development stages indicate rightward shifts. The value is in-the-money beyond the discovery phase. The fact that the option value has greater variability in later stages is due to increased uncertainty about time and investment and is therefore more risky. However, the risk is more than compensated by larger expected returns.

Sensitivities

The first sensitivity illustrates the impact of trait efficiency on the option values. Table 5 (upper and lower panel) illustrates trait efficiencies of 0.06 and 0.20 versus the base-case trait efficiency of 0.12. If DT corn is not as efficient (e.g., 0.06), the option values drop substantially. At regulatory submission, the option value declines from $132 to $56 million. With this reduced trait efficiency, there is a greater chance that the option value would be negative for each of the first four development phases. In this case, it is unlikely that the option would be exercised and extended to further R&D. If trait efficiency is greater than the base case (e.g., 0.20), the option values increase substantially. The mean value increases from $132 to $220 million at regulatory submission.

We also analyzed the impact of more acres planted to corn. The base case was 89 million acres on longer-term projections at that time. As sensitivity, we specified the area planted as 93 million acres. In this case, the value of the options increased from $1.7 to $2.0 million and from $132 to $139 million in the discovery and regulatory submission phases.

The third sensitivity introduces uncertainty regarding area planted and trait pricing. Specifically, we allowed the RRAC to range from 2 to 4, represented as a triangular distribution, and changed the sharing percentage of technology fees to a range uniformly distributed from 0.3 to 0.5. Interpretation of range of RRACs is that there is uncertainty about the risk aversion of growers (implying there

Table 5. Option Value Estimates for Each Development Phase ($ Millions)

Trait Efficiency	Parameter	Development Phase Discovery	Proof of Concept	Early Development	Advanced Development	Regulatory Submission
0.06	Mean	−1.1	−0.8	6.8	24.0	56.0
	Min	−4.1	−11.6	−13.1	−6.8	22.9
	Max	2.5	13.2	32.9	62.7	96.2
	StD	1.3	5.2	10.6	16.9	20.6
	Probability ≤ 0	0.86	0.69	0.21	0.01	0
Base case 0.12	Mean	1.7	15.6	42.4	82.3	132.3
	Min	−1.9	0.0	10.9	35.2	77.1
	Max	6.5	37.0	85.5	148.2	204.7
	StD	1.3	5.2	10.6	16.9	20.6
	Probability ≤ 0	0.09	0	0	0	0
0.20	Mean	4.9	34.4	83.5	149.5	220.2
	Min	0.1	12.7	37.6	80.0	135.9
	Max	11.5	68.4	152.2	257.3	245.8
	StD	1.7	7.9	16.6	26.4	33.0
	Probability ≤ 0	0	0	0	0	0

would be different market segments) and that there would be uncertainty on the amount of the value to growers that the agbiotechnology firm can capture. The other change allowed for the area planted to be random with ±5% uniformly distributed for each of six regions.

Results are shown in table 6. Compared to the base case (table 5), the mean option values increase due to a larger planted area. The standard deviation increases at each development phase, reflecting greater uncertainty in this scenario. The standard deviation increases from twenty-one to thirty-two in the regulatory-submission phase, and the CV increases from 0.16 to 0.22. All these results illustrate the impacts of greater uncertainty during the development phase and how it impacts the option value of trait development.

Managerial Implications

Ultimately, the purpose of valuing real options for R&D is to guide managerial decisions. These results can be used to illustrate the strategy implications. First, trait efficiency is very important. In practice, trait efficiency is not known until at least the early development phase. Trait-efficiency improvements increase the option values substantially. This is no doubt the reason why agbiotechnology companies spend considerable amounts of time identifying events with the greatest trait efficiency.

Second, risky variables are important and impact the option values as well as their likelihood of being in- or out-of-the-money. Increases in randomness can occur for a number of variables; the most important are likely adoption rates and trait values. The impact of this is increased chances that option values would not be in-the-money, resulting in a greater chance that management would not exercise the option.

Third, whether the option value is in-the-money should guide managers to continue. In the base case, the mean values of options are all positive, or in-the-money. Hence, managers would choose to exercise the option and continue. If the option value were negative, the decision would be to wait or abandon. In this case there is a chance (0.135) that the option would be out-of-the-money in the discovery phase (base case).

Table 6. Option Value Estimates with Greater Randomness in Area Planted and Trait Prices ($ Millions)

	Development Phase				
	Discovery	Proof of Concept	Early Development	Advanced Development	Regulatory Submission
Mean	2	18	48	91	144
Min	−2	−4	4	21	59
Max	8	50	117	208	293
StD	2	7	15	25	32
Probability ≤ 0	0.08	0.002	0	0	0

Finally, these results can be used to illustrate the virtue of real-option methodologies versus more conventional net-present-value methods. By ignoring options and their values, there is a greater tendency to under-value projects, which may result in an under-investment in R&D (Hayes and Abernathy, 1980; Hayes and Garvin, 1982; Trigeorgis, 2001; Tri). These points can be illustrated in these results. The binomial-option methodology suggests that the investment becomes in-the-money at later stages of development. In the base case, there are 0.135 chances the option value will be out-of-the-money during the discovery stage while, at the last stage of regulatory submission, there is a 90% chance the option value would be positive with a mean of $125 million. Initially, there is a 95% chance of the option value being less than $3.58 million, but later on there is a 95% chance of the option value being more than $94.7 million (90% chance between $94.7 million and $160 million). If the investment decision is made using net present value, the decision not to invest could have been made in the early stages. Viewing the decision as a real option avoids this choice. The option value becomes increasingly in-the-money at successive development stages (figure 3). Similarly, the greater uncertainty in trait efficiency would result in a chance of abandoning R&D in the early phases. In this case, there is a non-zero probability of loss during the first two development stages, in which case decision makers may have chosen to not to invest.

Summary and Implications

The valuation of research and development (R&D) is an important problem for many agribusinesses, particularly agbiotechnology. These companies spend large amounts of money and are subject to many sources of uncertainty. As a result, these decisions are very risky. Real options can be used to value R&D and capture these influences. As a methodology, real options have the advantage of capturing uncertainties and embedding managerial options during the development phases. In this case, agbiotechnology firms could spend in excess of $130 million over ten to twelve years to develop a trait with highly uncertain technological feasibility, value, and market penetration. Development of DT corn using genetic modification is a good illustration of these problems and opportunities.

We developed a stochastic, binomial real-option model to analyze this problem. Technically, we used a compound-call option with options to continue, wait, or abandon at each phase. The model captured a number of risk sources, including those related to development cost and time, trait efficiency, trait values, area planted, and adoption rates. The model was solved to derive option values, along with distributions about these values, at each phase of the R&D development process.

The results indicated that Prairie Gateway and Northern Great Plains regions would have the greatest value for DT corn. There is no doubt that agbiotechnology companies will be targeting these regions for adopting the DT trait. DT corn had positive expected values for the option value at each phase of the development process. In the base case, there was a slight chance the option value would be out-of-the-money during the discovery phase. In all other phases, the expected value was in-the-money. The results were highly sensitive with respect to trait efficiency and regarding the assumptions of randomness in some other important variables, notably trait values.

These results illustrate some important managerial implications. First, managers should use whether the option is in-the-money to guide their choice to continue to the next phase of research, wait, or abandon. Indeed, this methodology would have encouraged a company to continue at each phase, whereas a comparably constructed NPV analysis may have suggested not continuing at the discovery phase. Thus, capturing managerial options is critical. Second, trait efficiency is very important and likely illustrates why agbiotechnology companies spend so much time trying to identify the event that has the greatest impact.

Finally, there are a number of limitations and extensions for future research. The limitations are virtually all related to the random variables' distributions. While the random variables are not observable in practice, or to outside researchers, the use of risk methodologies can go a long ways toward capturing these impacts. There are a number of areas in which these methods could be expanded. One would be to apply them to other traits that are emerging (nitrogen-use efficiency, cold tolerance, shattering in canola, etc.). The second choice would be to analyze values for stacked traits, which would have to capture the correlated valuations of traits to growers. Finally, in a broader context, agbiotechnology firms (and R&D programs) are ultimately at varying stages of developing multiple traits for various commodities at the same time. In this case, strategies for evaluating among option values are appropriate, as suggested in Luehrman (1997).

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