An Analysis of the Pricing of Traits in the U.S. Corn Seed Market

by

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Abstract: This paper investigates the pricing of patented traits in the U.S. hybrid corn seed market under imperfect competition. In a multiproduct context, we first examine how substitution/complementarity relationships among products can affect pricing. This is used to motivate multi-product generalizations of the Herfindahl-Hirschman index (GHHI) capturing cross-market effects of imperfect competition on bundle pricing. The GHHI model is applied to pricing of conventional and patented biotech seeds in the US from 2000-2007. One major finding is that standard component pricing in biotech traits is soundly rejected in favor of subadditive bundle pricing. The econometric estimates show how changes in market structures (as measured by both own- and cross-Herfindahl indexes) affect U.S. corn seed prices.

Key Words: Component pricing, imperfect competition, seed, biotechnology

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The U.S. agricultural biotechnology and seed industries have experienced many changes over the last few decades. On the one hand, new seeds including biotech patented traits offer new prospects for increasing agricultural productivity. This has stimulated a rapid adoption of biotech seeds in the U.S. for corn, soybean and cotton. On the other hand, mergers and acquisitions in the seed industry have resulted in concentrated seed markets dominated by a few large biotech firms. This has raised some concern that market power and imperfect competition could lead biotech firms to charge high prices for the biotech seeds, with potential adverse effects on farmers' welfare. Biotechnology and genetic modifications have also stimulated product differentiation with patented traits being bundled with basic seed germplasm. Evaluating the pricing of such products under imperfect competition presents several challenges. One challenge is to evaluate the cross-markets impacts of market power under product differentiation. Another challenge is the empirical assessment of the pricing of bundled traits in biotech seed. A lack of available data has severely limited such investigations in previous research.[1]

This paper addresses these challenges with a focus on the analysis of the pricing of patented traits in the U.S. corn seed market. It makes three important contributions. First, we develop a pricing model of differentiated products under a quantity-setting game. In a multiproduct context, we show the linkages between pricing and substitution/complementarity relationships among products with different bundled characteristics. This is used to motivate multi-product generalizations of the Herfindahl-Hirschman index (hereafter GHHI), which capture cross-market effects of imperfect competition on bundle pricing. Second, the GHHIs are introduced in an econometric analysis of the determinants of bundle pricing. To our knowledge, this is the first econometric investigation using GHHI to estimate the linkages between imperfect

[1] In contrast, there is a rich body of analytical literature on bundle theory (e.g., Adams and Yellen 1976, McAfee et al. 1989, Fang and Norman 2006).

competition and multiproduct pricing. The model also allows for a test of standard component pricing (where the price of bundle is the sum of the prices of each individual component within the bundle). Third, we present an empirical application to the U.S. hybrid corn seed market using extensive survey data. The econometric estimates provide useful information on interactions between bundling and the exercise of market power.

Genetically modified (GM) corn acres account for about 80 percent of the total U.S. corn acreage in 2007. GM corn seed includes patented genetic traits (such as insect resistance and/or herbicide tolerance) patented by biotech firms. These traits can be introduced into the seed either separately, or bundled together when multiple genetic traits are "stacked". The proportion of U.S. corn acres planted with stacked seeds has gone from 2.1 percent in 2000 to 56.2 percent in 2007. Also, there has been a sharp increase in the number of traits being bundled. Single-trait GM corn seed was first commercialized in 1996. Two years later the double-stacked corn seed (i.e., the bundling of two traits) was introduced, followed by the introduction of the triple-stacked system, and then the quadruple-stacked system in around 2006. Moreover, corn seed with eight traits is expected to be released by Monsanto and Dow AgroScience by 2010.

The increased use of GM corn seeds has been associated with changing structure in the U.S. seed markets. After a flurry of horizontal and vertical mergers in the 1990s, the corn seed industry is now dominated by a few large biotech firms (Fernandez-Cornejo 2004). According to Graff, Rausser and Small (2003), these mergers have been motivated in part by the complementarities of assets within and between the agricultural biotechnology and seed industries. This indicates that trait bundling can be associated with cost reductions obtained from capturing economies of scope in the production of genetic traits. But bundling can also be part of a product differentiation strategy and price discrimination scheme intended to extract more profit

from farmers facing varying agro-climatic conditions. In this context, increased market concentration has raised concerns about adverse effects of imperfectly competitive pricing and the strategic use of bundling (Fulton and Giannakas 2001; Fernandez-Cornejo 2004). These issues suggest a need to investigate empirically the economics of pricing of hybrid corn seeds.

Our econometric analysis quantifies the linkages between different combinations of traits, changes in market concentrations, and hybrid corn seed pricing. For bundled biotech traits, we reject standard component pricing of biotech traits. We find strong evidence of subadditive bundle pricing, which is consistent with price discrimination strategies and scope economies in the production of bundle-traited seeds. The analysis evaluates the interactive role of market concentrations and complementarity/substitution in demand. We document the linkages between traditional and cross-market concentrations and seed prices. This is done by estimating Lerner indexes, which provide useful information on departures from marginal cost pricing. Our analysis also illustrates how changing market structures (e.g., from mergers) relate to seed prices.

The paper is organized as follows. The model section presents a conceptual framework of multiproduct pricing under imperfect competition. We then provide an overview of the U.S. corn seed market, followed by an econometric model of seed pricing, where the GHHIs reflect the exercise of market power. The estimation method and econometric results are then discussed and the empirical findings and their implications are reported. The conclusion section is at the last.

The Model

Consider a market involving a set $\mathbf{N} = \{1,...,N\}$ of N firms producing a set $\mathbf{T} = \{1,...,T\}$ of T outputs. Denote by $y^n \equiv (y_1^n,...,y_m^n,...,y_T^n) \in \Re_+^T$ the vector of outputs produced by the n-th firm, y_m^n being the m-th output produced by the n-th firm, $m \in \mathbf{T}$, $n \in \mathbf{N}$. The price-dependent demand

for the *m*-th output is $p_m(\sum_{n\in\mathbf{N}} y^n)$. The profit of the *n*-th firm is:

$\sum_{m\in\mathbf{T}}[p_m(\sum_{n\in\mathbf{N}} y^n)y_m^n]-C_n(y^n)$, where $C_n(y^n)$ denotes the *n*-th firm's cost of producing y^n.

Assuming a Cournot game and under differentiability, the profit maximizing decision of the *n*-th firm for the *m*-th output y_m^n satisfies

$$p_m+\sum_{k\in\mathbf{T}}\tfrac{\partial p_k}{\partial y_m^n}y_k^n-\tfrac{\partial C_n}{\partial y_m^n}\le 0, \tag{1a}$$

$$y_m^n\ge 0, \tag{1b}$$

$$\left(p_m+\sum_{k\in\mathbf{T}}\tfrac{\partial p_k}{\partial y_m^n}y_k^n-\tfrac{\partial C_n}{\partial y_m^n}\right)y_m^n=0. \tag{1c}$$

Equation (1c) is the complementary slackness condition. It applies whether the *m*-th output is produced by the *n*-th firm ($y_m^n > 0$) or not ($y_m^n = 0$). This is important for our analysis: (1c) remains valid irrespective of the firm entry/exit decision in the industry; and for an active firm, (1c) holds no matter how many of the *T* products the firm chooses to sell.

Below, we consider the case of linear demands where $p_k=\alpha_k+\sum_{m\in\mathbf{T}}(\alpha_{km}\sum_{n\in\mathbf{N}} y_m^n)$, with $\frac{\partial p_k}{\partial y_m^n}=\alpha_{km}$ and $\alpha_{mm}<0$. We also assume that the cost function takes the form $C_n(y^n)$ = $F_n(S^n)+\sum_{m\in\mathbf{T}}c_m y_m^n$, where $S^n=\{j\in\mathbf{T}: y_j^n>0\}$ is the set of positive outputs produced by the *n*-th firm. Here, $F_n(S^n)\ge 0$ denotes fixed cost that satisfies $F_n(\varnothing)$ = 0. And $\sum_{m\in\mathbf{T}}c_m y_m^n$ denotes variable cost, with constant marginal cost $\frac{\partial C_n(y^n)}{\partial y_m^n}=c_m$, $m\in\mathbf{T}$ for all $n\in\mathbf{N}$. Note that the presence of fixed cost (where $F_n(S^n)$ > 0 for $S^n\ne\varnothing$) implies increasing returns to scale. In this situation, marginal cost pricing would imply negative profit and any sustainable equilibrium must be associated with departures from marginal cost pricing. Fixed cost can also capture the presence of economies of scope. This would occur when $F_n(\mathbf{T}_a)+F_n(\mathbf{T}_b)>F_n(\mathbf{T}_a\cup\mathbf{T}_b)$ for some

$\mathbf{T}_a \subset \mathbf{T}$ and $\mathbf{T}_b \subset \mathbf{T}$, i.e. when the joint production of outputs $y_a^n = \{y_j^n : j \in \mathbf{T}_a\}$ and $y_b^n = \{y_j^n : j \in \mathbf{T}_b\}$ reduces fixed cost (Baumol et al., 1982, p. 75). A relevant example is the case of an R&D investment contributing to the joint production of y_a^n and y_b^n.

Assuming that the aggregate output of the *m*-th product is positive, $Y_m = \sum_{n \in \mathbf{N}} y_m^n > 0$, define $s_m^n = \frac{y_m^n}{Y_m} \in [0,1]$ as the market share of the *n*-th firm for the *m*-th product. Dividing equation (1c) by Y_m and summing across all $n \in \mathbf{N}$ yield

$$p_m = c_m - \sum_{k \in \mathbf{T}} (\alpha_{km} \sum_{n \in \mathbf{N}} s_k^n s_m^n Y_k), \tag{2}$$

which can be alternatively written as

$$p_m = c_m - \sum_{k \in \mathbf{T}} \alpha_{km} H_{km} Y_k, \tag{3}$$

where Y_k is the aggregate output of the *k*-th product, and $H_{km} \equiv \sum_{n \in \mathbf{N}} s_k^n s_m^n$, with $m, k \in \mathbf{T}$.

Equation (3) is a pricing equation for the *m*-th product. It is a structural equation in the sense that both price p_m and the market shares in the H_{km}'s are endogenous (as they are both influenced by firms' strategies). Yet, equation (3) provides useful linkages between price and market structure. It shows that the exercise of market power in (3) is given by

$$M_m = -\sum_{k \in \mathbf{T}} \alpha_{km} H_{km} Y_k, \tag{4}$$

which reflects departures from marginal cost pricing. A simple way to characterize this departure is through the Lerner index: $L_m = \frac{p_m - c_m}{p_m}$, where c_m is marginal cost. The Lerner index L_m measures the proportion by which the *m*-th output price exceeds marginal cost. It is zero under marginal cost pricing, but positive when price exceeds marginal cost. The Lerner index provides a simple characterization of the strength of imperfect competition (where the firm has market

power and its decisions affect market prices). From equations (3) and (4), the Lerner index can be written as $L_m = \frac{M_m}{p_m}$. This makes it clear that M_m in (4) gives a per-unit measure of price enhancement beyond marginal cost. Equation (4) also provides useful information on the structural determinants of M_m. Indeed, while $H_{km} \in [0, 1]$, note that $H_{km} \to 0$ under perfect competition (where the number of active firms is large) and $H_{km} = 1$ under monopoly (where there is single active firm). In other words, the term M_m in (4) captures the effects of imperfect competition and the exercise of market power on prices.

When $k = m$, note that H_{mm} is the traditional Herfindahl-Hirschman index (HHI) providing a measure of market concentration. The HHI is commonly used in the analysis of the exercise of market power (e.g., Whinston 2008). Given $\alpha_{mm} < 0$, equation (3) indicates that an increase in the HHI H_{mm} (simulating an increase in market power) is associated with an increase in the Lerner index L_m and in price p_m. As a rule of thumb, regulatory agencies have considered that $H_{mm} > 0.1$ corresponds to concentrated markets where the exercise of market power can potentially raise competitive concerns (e.g., Whinston 2008).[2]

Equation (3) extends the HHI to a multiproduct context. It defines H_{km} as a generalized Herfindahl-Hirschman index (GHHI). When $k \neq m$, it shows that a rise in the "cross-market" GHHI H_{km} would be associated with an increase (a decrease) in the Lerner index L_m and in the price p_m if $\alpha_{km} < 0$ (> 0). This indicates that the signs and magnitudes of cross demand effects $\alpha_{km} = \frac{\partial p_k}{\partial y_m^n}$ affect the nature and magnitude of departure from marginal cost pricing. Following

[2] The markets shares are often expressed in percentage term in the calculation of the Herfindahl-Hirschman index. Then, the rule becomes $H_{mm} > 1000$ (Whinston 2008).

Hicks (1939), note that $\alpha_{km} = \frac{\partial p_k}{\partial y_m^n} < 0$ (> 0) when products *k* and *m* are substitutes (complements) on the demand side, corresponding to situations where increasing y_m^n tends to decrease (increase) the marginal value of y_k^n. The terms $\{H_{km} : k \neq m\}$ in equation (3) show how the nature of substitution or complementarity among outputs on the demand side (through the terms α_{km}) influences the effects of market concentration on the Lerner index and prices[3]: a rise in H_{km} would be associated with an increase (a decrease) in the Lerner index L_m and in the price p_m when y_k and y_m are substitutes (complements).

Note that equation (3) applies to general multiproduct pricing in a Cournot game under imperfect competition. It includes as a special case the pricing of bundled goods differentiated by their characteristics. In a way consistent with previous research (e.g., Adams and Yellen 1976; Venkatesh and Kamakura 2003; Fang and Norman 2006), it shows that the exercise of market power in bundling and bundle pricing can be complex. This indicates a need to assess empirically how the bundling of product characteristics interacts with market structures to affect pricing. This issue is explored next in the context of the U.S. corn seed market.

The U.S. Corn Seed Market

Our analysis relies on a large, extensive data set providing detailed information on the U.S. corn seed market. The data were collected by **dmr**kynetec [hereafter dmrk]. The dmrk data come from a stratified sample of U.S. corn farmers surveyed annually from 2000 to 2007.[4] The survey

[3] Our model provides a more general framework in analyzing the role played by substitution/ complementarity in multiproduct pricing under imperfect competition than Venkatesh and Kamakura (2003), who investigate such issues only in a monopolistic setup.

[4] Data prior to 2000 is not available from dmrk. The survey is stratified to over-sample producers with large acreage. The sampling weights are constructed using the farm census data.

provides farm-level information on corn seed purchases, corn acreage, seed types and seed prices. It was collected using computer assisted telephone interviews. On average about 40-50% of the farms surveyed each year remain in the sample for the next year. For 2000-2007, the dmrk data contains 168,862 observations on individual corn seed purchases from 279 USDA crop reporting districts (CRD)[5] in 48 states. A total of 38,617 farms were surveyed during 2000-2007, with each farm on average purchasing four to five different corn seed each year.

Since farmers typically buy their seeds locally, our analysis defines the "local market" at the CRD level. On average each farm purchased four to five different seeds each year[6]. To guarantee reliable measurement of market concentrations, we focus our analysis on those CRDs in the slightly expanded Corn Belt regions with more than ten farms sampled every year between 2000 and 2007. In total, our data contain 139,410 observations from 80 CRDs in 12 states.[7]

Starting in the 1930s, the development and diffusion of hybrid corn transformed the U.S. seed industry and contributed to the dominant role played by private seed companies. The dmrk data show that about 300 seed companies operate in the current U.S. corn seed market. However, only six biotech firms are involved,[8] four of which own subsidiary corn seed companies.[9]

Currently there are two major groups of genes/traits in the GM seed market: insecticide resistance designed to reduce yield damages caused by insects; and herbicide tolerance designed to reduce yield reductions from competing plants (weeds). For corn, the insect resistance traits

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[5] A crop-reporting district (CRD) is defined by the U.S. Department of Agriculture to reflect local agro-climatic conditions. In general, a CRD is larger than a county but smaller than a state.

[6] Due to the fast turnover in the seed market, farmers may try new hybrid seeds every year, thus would purchase more than one hybrid seed type for their field. In addition, the U.S. EPA requires that farmers maintain at least 20 percent of their cropland for "non-insect resistant" hybrid seeds.

[7] They are: IL, IN, IA, KS, KY, MI, MN, MO, NE, OH, SD, and WI.

[8] They are: Monsanto, Syngenta, Dow AgroSciences, DuPont, Bayer CropScience, and BASF.

[9] While one of the rest two firms has already entered the cotton seed market, the dmrk data show that it has not entered (yet) the U.S. corn seed market.

focus on controlling damages caused by two insects: the European corn borer (*ECB*),[10] and rootworms (*RW*).[11] The herbicide tolerance (*HT*) traits work with corresponding herbicides. After adopting the *HT* traited seed technology, farmers can apply the relevant herbicide to the field, which kills the weeds without damaging the traited crop. Some biotech seeds contain only one of these traits, while the bundled seeds contain multiple traits from some combination of the two groups of traits.

Figure 1 shows the evolution of corn acreage shares reflecting adoption rates in the US from 2000 to 2007, for conventional seed, single-trait biotech seed, double-stacking biotech seed, triple-stacking biotech seed, and quadruple-stacking biotech seed. The conventional seed's acreage share has decreased rapidly over the past eight years: from 67.5% in 2000 to 20.6% in 2007. Table 1 illustrates the average price of different hybrid corn seeds ($ per bag) from 2000 to 2007. It indicates that biotech traits tend to add value to the conventional germplasm, and that multiple stacking/bundling is worth more than single stacking. The information presented in figure 1 and table 1 is at the national level, which masks important spatial market differences. For example, while single-trait biotech seeds had a U.S. market share of 30% in 2000, the dmrk data show that conventional seeds still dominated many local markets. And while the U.S. conventional seed's market share was 20.6% in 2007, some local markets were completely dominated by biotech seeds. This indicates the presence of spatial heterogeneity in the U.S. corn seed market. As shown below, such heterogeneity also applies to seed prices.

[10] The European corn borer is a major pest of corn in North America and Europe. Yield loss due to *ECB* has been estimated to average about five percent, although damages can vary widely both over time and over space.

[11] Yield loss due to corn rootworms damages average around five percent in the US, amounting to about $800 million of reduced income for U.S. corn growers.

Figure 1. Percentage of U.S. Acreage Planted in Conventional and GM corn seed , 2000 – 2007.

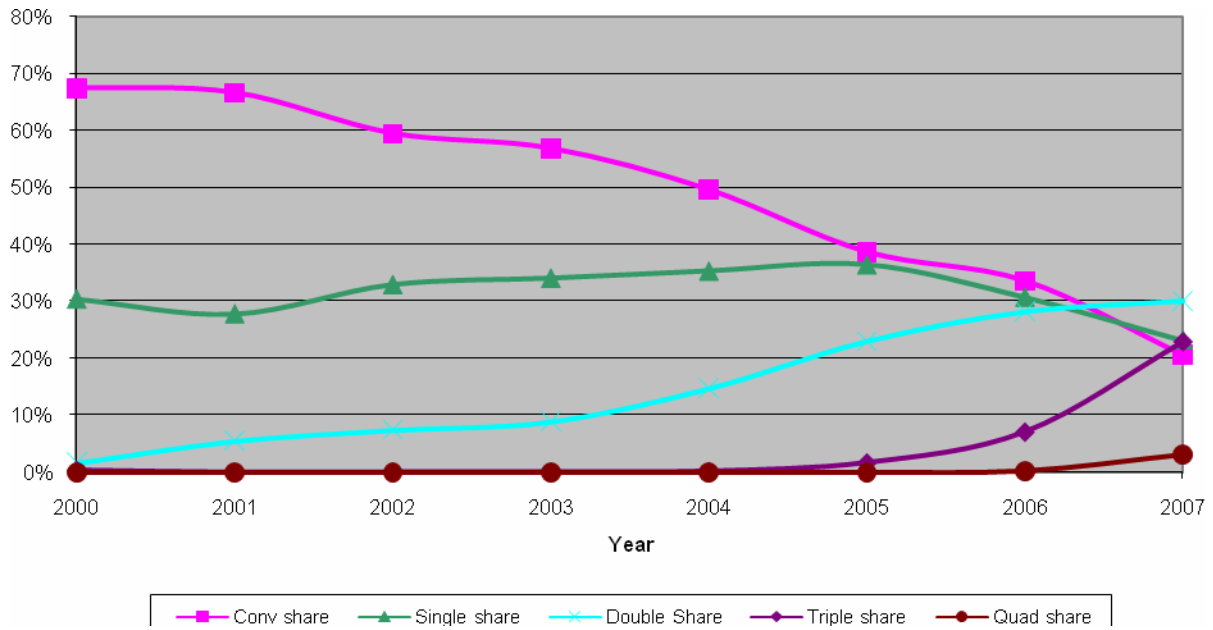

Table 1. Average price for different seeds ($ per bag), 2000 - 2007

Year	Conventional	*ECB Single*	*RW Single*	*HT Single*	*Double*	*Triple*	*Quadruple*
2000	79.37	100.24	n/a	87.34	95.21	100.95	n/a
2001	80.73	103.77	n/a	89.85	100.43	105.29	n/a
2002	81.81	103.91	n/a	89.08	103.19	94.64	n/a
2003	83.79	104.93	114.88	94.73	108.78	82.10	n/a
2004	86.42	108.61	120.49	98.88	113.68	112.21	n/a
2005	86.96	104.46	114.52	101.50	114.49	123.78	n/a
2006	91.36	109.69	116.67	109.93	123.03	139.21	131.29
2007	93.53	111.36	121.07	114.67	124.71	133.02	140.03
Total	84.29	105.37	117.33	101.51	118.25	133.47	139.60

Econometric Specification

Our analysis of the determinants of corn seed prices builds on equation (3). As derived, equation (3) is a structural equation reflecting the determinants of pricing under imperfect competition in a multi-product framework. As discussed in the model section, fixed cost can generate economies of scope. Economies of scope are relevant here as R&D investment likely generates synergies in

the production of bundled/stacked seeds. This would in turn affect bundle pricing. Also, the effects of imperfect competition on price can be expected to depend on the nature of substitution/complementarity across bundles. Below, we specify a modified version of (3) that reflects the effects of both bundling and market power on corn seed price.

Consider for the case of seeds exhibiting different genetic characteristics. Partition the set of seeds into mutually exclusive types. Let $K_i \in \{0, 1\}$ be a dummy variable for a seed of the *i*-th type, $i = 1, \ldots J$. Let $i = 1$ characterize conventional seed, and let $\mathbf{Q} \equiv \{2, ..., J\}$ denote the set of genetic traits associated with biotech seeds. Thus, $K_1 = 1$ for conventional seeds. Each biotech seed includes at least one genetic trait in the set **Q**, with $K_i = 1$ if the seed includes the genetic traits of the *i*-th type either individually or stacked with other traits, $i \in \mathbf{Q}$, and $K_i = 0$ otherwise. In the absence of bundling/stacking (where each seed can be of only one type), the *K*'s would satisfy $\sum_{i=1}^{J} K_i = 1$. However, in the presence of stacking, some biotech seeds may include the genetic traits of more than one type, implying that $\sum_{i=1}^{J} K_i \geq 1$. Therefore, evaluating the effects of the genetic characteristics on seed prices requires a flexible specification that can capture bundling/stacking effects.

We start with a standard model in which each purchase observation is at the farm-level and the price of a seed varies with its characteristics (e.g., following Rosen 1974). The price *p* represents the net seed price paid by farmers (in $ per bag).[12] Consider the hedonic equation representing the determinants of the price *p* for a seed of characteristics $\{K_1, K_2, ..., K_J\}$:

$$p = \beta + \sum_{i \in \{1,...,J\}} \delta_i K_i + \sum_{\substack{j \in \mathbf{Q} \\ j > i}} \sum_{i \in \mathbf{Q}} \delta_{ij} K_{ij} + \sum_{\substack{z \in \mathbf{Q} \\ z > j}} \sum_{\substack{j \in \mathbf{Q} \\ j > i}} \sum_{i \in \mathbf{Q}} \delta_{ijz} K_{ijz} + \sum_{\substack{r \in \mathbf{Q} \\ r > z}} \sum_{\substack{z \in \mathbf{Q} \\ z > j}} \sum_{\substack{j \in \mathbf{Q} \\ j > i}} \sum_{i \in \mathbf{Q}} \delta_{ijzr} K_{ijzr} + \boldsymbol{\varphi}\mathbf{X} + \varepsilon, \qquad (5a)$$

[12] We also estimated a log specification of the price equation. The econometric results were qualitatively similar to the ones reported below.

where **X** is a vector of other relevant covariates, and ε is an error term with mean zero and constant variance. In equation (5a), K_{ij} is a dummy variable for double-stacking the *i*-th and *j*-th genetic type. Similarly, K_{ijz} and K_{ijzr} are dummy variables representing respectively triple-stacking and quadruple-stacking.[13]

For conventional seeds and single-trait seeds, the dummy variables K_{ij}, K_{ijz} and K_{ijzr} are all zero. This implies that the coefficients δ_{ij}, δ_{ijz}, and δ_{ijzr} in (5a) capture the effects of bundling on seed price. The dmrk data reveal that trait bundling is common, which allows us to test for its price impacts. One important special case occurs when $\delta_{ij} = \delta_{ijz} = \delta_{ijzr} = 0$, which corresponds to standard component pricing. Here, the price of seed is just the sum of the value of its genetic components (as captured by $\sum_i \delta_i K_i$, with δ_i measuring the unit value of the *i*-th genetic material). When the parameters δ_{ij}, δ_{ijz}, and δ_{ijzr} are not all zero, equation (5a) allows for non-linear pricing associated with bundled goods under stacking.

In general, the parameters δ_{ij}, δ_{ijz}, and δ_{ijzr} can be either positive or negative. When positive, these parameters would reflect super-additive bundle pricing. This could occur when component demands are complementary, i.e., when adding a trait to an existing trait system increases consumer's valuation for the stacked system more than the marginal value of the additional trait. Alternatively, negative parameters would correspond to sub-additive bundle pricing. The price of bundled goods would then be "discounted" compared to component pricing.

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[13] Note that the *K*'s in (5a) satisfy $\sum_{i\in\{1,\ldots,J\}} K_i - \sum_{\substack{j\in\mathbf{Q}\\ j>i}}\sum_{i\in\mathbf{Q}} K_{ij} - 2\sum_{\substack{z\in\mathbf{Q}\\ z>j}}\sum_{\substack{j\in\mathbf{Q}\\ j>i}}\sum_{i\in\mathbf{Q}} K_{ijz} - 3\sum_{\substack{r\in\mathbf{Q}\\ r>z}}\sum_{\substack{z\in\mathbf{Q}\\ z>j}}\sum_{\substack{j\in\mathbf{Q}\\ j>i}}\sum_{i\in\mathbf{Q}} K_{ijzr} = 1$, implying that they are perfectly collinear with the intercept. To deal with this issue below, we set $\delta_1 = 0$ in (5a), meaning that the intercept reflects the price of conventional seeds and that the other δ parameters measure price differences relative to conventional seeds.

This could happen under two scenarios. First, this could be associated with economies of scope on the production side, if the joint production of bundled goods leads to a cost reduction that gets translated into lower bundle price. Second, this could be associated with price discrimination on the demand side, if discounting the price of a bundled good can help increase firm profit. In general, equation (5a) provides a framework to analyze the nature of bundle pricing.

Next, as shown in equation (3), we introduce market power effects in (5a) by specifying

$$\delta_i = \delta_{0i} + \delta_{ii} H_{ii}, \tag{5b}$$

where $H_{ii} \equiv \sum_{n \in \mathbf{N}} s_i^n s_i^n$ is the HHI (s_i^n being the market share of the *n*-th firm in the market for the *i*-th seed type) measuring market concentration in the *i*-th market. We further specify

$$\beta = \beta_0 + \sum_{\substack{j \in \mathbf{Q} \\ j > i}} \sum_{i \in \mathbf{Q}} \beta_{ij} H_{ij} K_i + \sum_{\substack{j \in \mathbf{Q} \\ j > i}} \sum_{i \in \mathbf{Q}} \beta_{ji} H_{ji} K_j, \tag{5c}$$

where $H_{ij} \equiv H_{ji} \equiv \sum_{n \in \mathbf{N}} s_i^n s_j^n$ being the cross-market GHHI discussed in the model section and measuring concentration for firms operating in the market for both *i*-th and *j*-th characteristics. With this specification, the coefficient of the traditional HHI, $\delta_{ii} \neq 0$, would reflect market power related to the *i*-th characteristic, while the coefficient of the GHHI, $\beta_{ij} \neq 0$ or $\beta_{ji} \neq 0$, would reflect the exercise of market power across characteristics.

Since the HHI and the GHHI's are zero under competitive conditions, it follows from equations (4) and (5a)-(5c) that the effect of market power on price is given by

$$M = \sum_{i \in \{1,\ldots,J\}} \delta_{1i} H_{ii} K_i + \sum_{\substack{j \in \mathbf{Q} \\ j > i}} \sum_{i \in \mathbf{Q}} \beta_{ij} H_{ij} K_i + \sum_{\substack{j \in \mathbf{Q} \\ j > i}} \sum_{i \in \mathbf{Q}} \beta_{ji} H_{ji} K_j. \tag{6}$$

In a way similar to equation (4), equation (6) provides a representation of the linkages between imperfect competition and pricing. As noted in the model section, the term *M* in (6) measures the difference between price and marginal cost. It can be used to obtain the associated

Lerner index $L = \frac{M}{p}$. When positive, M reflects the price enhancement associated with imperfect competition.

Our analysis is based on five seed characteristics (J = 5): Conventional $(K_1 = 1)$; insect resistance trait ECB $(K_2 = 1)$; insect resistance trait RW $(K_3 = 1)$; herbicide tolerance trait $HT1$ $(K_4 = 1)$; and herbicide tolerance trait $HT2$ $(K_5 = 1)$. Note that this distinguishes between two types of herbicide tolerance: $HT1$ and $HT2$. The reason is that, in our sample, $HT1$ and $HT2$ are sometimes stacked/bundled together. This implies that farmers see $HT1$ and $HT2$ as being different (otherwise, no farmer would pay extra for a second herbicide tolerant technology).

Our model specification allows us to estimate the pricing of each seed type along with stacking/bundling effects. To illustrate, from (5a)-(5c), the price equation for conventional seed $(K_1 = 1)$ is

$$p_1 = \beta_0 + \delta_{01} + \delta_{11} H_{11} + \sum_{j=2}^{5} \beta_{1j} H_{1j} + \boldsymbol{\varphi}\mathbf{X} + \varepsilon. \tag{7a}$$

For a seed marketed with a single ECB trait ($K_2 = 1$), the price equation becomes

$$p_2 = \beta_0 + \delta_{02} + \delta_{22} H_{22} + \beta_{21} H_{21} + \sum_{j=3}^{5} \beta_{2j} H_{2j} + \boldsymbol{\varphi} \cdot \mathbf{X} + \varepsilon. \tag{7b}$$

And for a double-stacking seed with an insect resistance trait (ECB) and our first herbicide tolerance trait ($HT1$) $(K_2 = 1, K_4 = 1,$ and $K_{24} = 1)$, the price equation is

$$p_{24} = \beta_0 + \delta_{02} + \delta_{04} + \delta_{24} + \delta_{22} H_{22} + \delta_{44} H_{44} + \beta_{21} H_{21} + \sum_{i=1}^{3} \beta_{4i} H_{4i} + \sum_{j=3}^{5} \beta_{2j} H_{2j} + \beta_{45} H_{45} + \boldsymbol{\varphi}\mathbf{X} + \varepsilon\,. \tag{7c}$$

Comparing equations (7b)-(7c) reveals how our model captures price differences between single-trait seed and bundled/stacked seeds. It shows how both stacking and market concentration affect pricing. Equation (7c) contains all the dummy variables reflecting

stacking/bundling of traits along with their interaction effects with the traditional HHI's: H_{ii}. It also contains the parameters linking price to the generalized cross market GHHI's: H_{ij}, $i \neq j$. Note that market share information is contained in both the traditional and cross Herfindahl indexes. This means that the effects of market concentration and imperfect competition on prices are complex. Evaluating these effects will be addressed in the implications section.

The relevant covariates in **X** include location, a time trend, each farm's total corn acreage, and binary terms covering the range of how each purchase was sourced. Location is represented by state dummy variables, along with the longitude and latitude of the county where the farm is located. These variables capture spatial heterogeneity in farming systems and agro-climatic conditions (including the length of the growing season). The latitude and longitude variables are specified in both linear and quadratic forms, reflecting possible non-linearity in their effects. For example, according to Griliches (1960), the corn seed industry first developed new hybrids that were best adapted to land in the center of the Corn Belt due to profitability consideration. It is likely that the same path is followed in the biotech seed development, which may result in a significant difference in seed prices between the center and fringe regions. The time trend is included to capture the advances in hybrid and genetic technology through the years of the study. Farm acreage captures possible price discrimination effects related to farm size. While there are a total of 16 different purchasing sources, most seeds are purchased through "Farmer who is a dealer or agent" (33.1%), followed by "Direct from seed company or their representatives" (29%), and "Myself, I am a dealer for that company" (16.1%). Note that a farmer may choose multiple sources to buy his seeds. Including source of purchase as an explanatory variable in (5a) captures possible price discrimination schemes affecting the seed price paid by farmers.

The market share of biotech seeds has increased significantly during the years of our study (see figure 1). In many cases, we found "entry" and "exit" of traited seeds in some local markets. In order to investigate whether entry/exit may affect seed prices beyond the *H* effects, we also introduce entry/exit variables in the specification (5a). In our data, we observe local exits in the conventional seed (K_1) markets. We also observe local entry in the *HT*1 trait (K_4) markets, the *ECB* trait (K_2) markets and the *RW* trait (K_3) markets. To capture entry-exit effects on seed price, the following binary terms are included: *Post-exit*1 = 1, when $H_{11} = 0$; *Pre-entry*2 = 1 when $H_{22} = 0$; *Pre-entry*3 = 1 when $H_{33} = 0$; and *Pre-entry*4 = 1 when $H_{44} = 0$.[14]

Estimation

Table 2 reports summary statistics of key variables used in the analysis. The mean values of H_{ii}'s show that the conventional seed markets are quite concentrated, but are considerably less concentrated than the biotech trait markets. Each CRD is presumed to represent the relevant market area for each transaction; thus, all *H* terms are calculated at that level. Conducting market concentration analysis at the CRD level allows us to evaluate the possibility that seed companies recognize localized market power for seeds with favorable performance parameters under various agro-climatic conditions. For the 80 CRDs covering the eight years of our data, the average conventional seed HHI is 0.242, which is well above the Department of Justice's threshold of 0.18 for identifying "significant market power". The average HHI for the three biotech seeds markets is over 0.80.

[14] Note that we do not construct an event dummy for K_5, as we do not observe any pattern of entry or exit for this trait.

One econometric issue in the specification (5a)-(5c) is the endogeneity of the *H*'s. Both market concentrations (as measured by the *H*'s) and seed pricing can be expected to be jointly determined as they both depend on firm strategies in the seed market. To the extent that parts of the determinants of these strategies are unobserved by the econometrician, this would imply that the *H*'s are correlated with the error term in equation (5a). In such situations, least-squares estimation of (5a)-(5c) would yield biased and inconsistent parameter estimates (due to endogeneity bias). The solution is to consider estimating equation (5a)-(5c) using an instrumental variable (IV) estimation method that corrects for endogeneity bias. To address this issue, we first test for possible endogeneity of the *H*'s using a *C* statistic calculated as the difference of two Sargan statistics (Hayashi 2000, p. 232). Under the null hypothesis of exogeneity of the *H*'s, the *C* statistic is distributed as Chi-square with degrees of freedom equal to the number of variables tested. The test is robust to violations of the conditional homoscedasticity assumption (Hayashi 2000, p. 232).[15] In our case, the *C* statistic is 200.16, showing strong statistical evidence against the null hypothesis of exogeneity of the *H*'s.

The presence of endogeneity motivates the use of an instrumental variable (IV) estimator. We used the lagged value of each *H* and the lagged value of the market size for each trait (including the conventional seed) as instruments. The use of lagged values reflects the time required to grow the seeds, as seed companies typically make production decisions a year ahead of the marketing decisions. Indeed these lag values are part of the information set available to the seed companies at the time of their production decisions. The Hansen over-identification test is not statistically significant, indicating that our instruments appear to satisfy the required

[15] Under conditional homoskedasticity, the *C* statistic is numerically equivalent to a Hausman test statistic.

orthogonality conditions. On that basis, equation (5a)-(5c) was estimated by two-stage-least-square (2SLS). Further evaluation of these instruments is presented below.

Table 2. Summary statistics

Variable	Number of observations[a,b]	Mean	Standard Deviation	Minimum	Maximum
Price ($)	139410	99.61	23.61	3	230
Farm size (acre)	30273	489.48	587.87	5	15500
Longitude	30273	91.59	4.783	80.75	103.76
Latitude	30273	41.71	2.010	36.71	46.98
H_{11}	639	0.242	0.152	0.067	1
H_{22}	639	0.769	0.188	0.337	1
H_{33}	313	0.907	0.150	0.430	1
H_{44}	639	0.772	0.175	0.434	1
H_{12}	601	0.085	0.070	0.99E-04	0.518
H_{13}	291	0.108	0.088	1.10E-03	0.632
H_{14}	580	0.075	0.079	9.58E-05	0.526
H_{23}	312	0.761	0.169	0.172	1
H_{24}	617	0.577	0.261	0.010	1
H_{34}	311	0.785	0.198	0.056	1

[a]/ The data contain 139410 observations from CRDs spanning 8 years (2000-2007). Each farm purchases multiple seeds, therefore the number of observations for farm size is the total count of farms per year. The longitude and latitude information is based on the county level measurement for each farm.

[b]/ For the market concentration measurements *H*'s, we only report the summary statistics of those non zeros at the CRD level, therefore the number of observations is at most 80× 8 = 640.

A second pretest was to evaluate the model for the effects on prices from unobserved heterogeneity across farms (e.g., unobserved pest populations). A Pagan-Hall test[16] found strong evidence against homoscedasticity of the error term in (5a). As reported earlier, each farm purchases on average four to five different seeds. Some large farms actually purchase up to 30 different hybrid seeds in a single year. Unobserved farm-specific factors affecting seed prices are expected to be similar within a farm (although they may differ across farms). This suggests that

[16] Compared to the Breusch-Pagan test, the Pagan-Hall test is a more general test for heteroscedasticity in an IV regression, which remains valid in the presence of heteroscedasticity (Pagan and Hall 1983).

the variance of the error term in (5a) would exhibit heteroscedasticity, with clustering at the farm level. On that basis, we relied on heteroscedastic-robust standard errors under clustering at the farm level in estimating equation (5a)-(5c).

Additional tests of the validity of the instruments were conducted. In the presence of heteroscedastic errors, we used the Bound et al. (1995) measures and the Shea (1997) partial R^2 statistic to examine the possible presence of weak instruments. The F-statistics testing for weak instruments were large (i.e., much above 10). Following Staiger and Stock (1997), this means that there is no statistical evidence that our instruments are weak. Finally, The Kleibergen-Paap weak instrument test was conducted (Kleibergen and Paap, 2006),[17] yielding a test statistic of 5.81. Using the critical values presented in Stock and Yogo (2005), this indicated again that our analysis does not suffer from weak instruments.

Empirical Results

Equation 5(a)-(5c) is estimated using 2SLS, with heteroscedastic-robust standard errors under clustering. We first tested whether the cross-market GHHI impact is symmetric: H_0: $\beta_{ij} = \beta_{ji}$, where the β's are the coefficients of the corresponding GHHI's. Using a Wald test, we fail to reject the null hypothesis for H_{13}. On that basis, we imposed the symmetry restriction for H_{13} in the analysis presented below.

Table 3 reports the results. For comparison purpose, the ordinary least square (OLS) estimation results are also reported. The OLS estimates of the market concentration parameters differ substantially from the 2SLS results. This reflects the endogeneity of our market concentration measures (and its associated bias). Our discussion below focuses on the 2SLS

[17] Note that the Kleibergen-Paap test is a better choice compared to the Cragg-Donald test for weak instruments: the former remains valid under heteroscedasticity (while the latter one does not).

estimates as IV/2SLS estimation corrects for endogeneity bias. We first discuss the price impacts associated with introducing single biotech traits. This builds toward a broader assessment of the more complex issues related to the marginal price impacts derived from the stacking of traits and from the role that market power has shifting rent between farmers and the seed industry. In the implications section, simulations of the Illinois corn seed market provides additional insights about the interactive forces that derive from biotechnology.

Characteristics effects: Compared to conventional seeds, the results show that the insertion of single biotech traits led to sizeable seed price premiums in three of the four traits considered. The coefficients of the terms K_2 (*ECB*), K_3 (*RW*) and K_5 (*HT*2) are each positive and statistically significant. They are respectively $25.64, $46.06, and $9.63 per bag, suggesting the presence of significant premiums for these biotech traits. The coefficients of K_4 (*HT*1) and K_5 (*HT*2) differ, providing evidence of differences between the two herbicide-tolerant traits *HT*1 and *HT*2. The coefficient of K_4 (*HT*1) is negative but not statistically significant. However, note that the *K*'s also appear in interaction with the *H*'s in (5a)-(5c). This means that coefficients of the *K's* alone provide only partial information on how prices vary across seed types. The magnitude of the price premium across seed types will be analyzed in more detail later.

The coefficients of the terms K_{ij}, K_{ijz}, and K_{ijzr} provide useful information on the effects of trait bundling on seed price. All of the stacking coefficients except for K_{35} are negative and statistically significant. The coefficient for K_{35} is positive but not statistically significant. As discussed in the econometric specifications section, component pricing is associated with the null hypothesis that all stacking coefficients are zero. Using a Wald test, the null hypothesis that the coefficients of stacking effects are all zero is strongly rejected. This provides convincing evidence against component pricing of biotech traits in the corn seed market. The negative and

significant stacking effects also indicate the prevalence of subadditive pricing of corn seed in their individual components. Subadditive pricing may be driven by price discrimination associated with demand heterogeneity (higher prices being associated with more inelastic demands). But the fact that all of the stacking coefficients are negative indicates the likely presence of economies of scope in the production of bundled/stacked seeds. This would be consistent with synergies in R&D investment (treated as fixed cost) across stacked seeds. For example, a given R&D investment can contribute to the production of multiple seed types, meaning that bundling can help reduce the overall cost of producing seeds. In this context, the subadditivity of prices would reflect the fact that seed companies share with farmers at least some of the benefits of scope economies.

Market concentration effects: The model incorporates market share information about each of the trait using the traditional Herfindahl indexes H_{ii} along with generalized cross-Herfindahl indexes H_{ij} as given in equations (5a)-(5c). Here, we discuss the partial effects of concentration and withhold a global assessment of market concentration until the implications section.[18] The partial effects of changes to the traditional Herfindahl indexes for each trait are presented in the first four rows of the "Market concentration effects". In this context, our estimates indicate that an increase in market concentration for conventional seeds (as measured by H_{11}) has a positive and statistically significant association with the price of conventional seeds. More specifically, a one-point increase in H_{11} is associated with a $14.81 per bag increase in the price of conventional seeds. The partial effect of concentration in the *RW* trait market

[18] We do not observe non-zero H_{15} because no firm that operates in *HT*2 market sells a conventional seed. Similar situations arise for H_{25}, H_{35} and H_{45}. When present, H_{55} =1 because only one firm operates in this trait market.

(H_{33}) and the *HT*1 trait market (H_{44}), were also positive and statistically significant: A one-point increase in H_{33} (H_{44}) is associated with a $32 ($14.92) per bag increase in the price of *RW* (*HT*1) seeds. Finally, the concentration effect in the *ECB* trait market is negative but not statistically significant.

We have shown in the model section that the effects of cross-market concentration H_{ij}, $i \neq j$, depend on the substitutability/complementarity relationship between traits *i* and *j*. We expect that an increase in the cross-market concentration H_{ij} will be associated with a rise (decrease) in the price if the two components are substitutes (complements).

Of the five cross GHHI's that involves conventional seed ($H_{12}, H_{21}, H_{13}, H_{14}, H_{41}$), only the coefficients on H_{12} (conventional market share crossed with *ECB* market share) and H_{41} (conventional market share crossed with *HT*1 market share) are statistically significant. The positive effect of both coefficients suggests that the *ECB* trait is viewed as a substitute for the conventional seed from the perspective of non-GM farmers; and the conventional seed is viewed as a substitute for the *HT*1 trait for the *HT*1 traited seed adopters. This is plausibly explained by the presence of a "yield drag" associated with adding a trait into a seed (Avise 2004, p. 41), which would induce some substitution in demand between this trait and conventional seed.

All the cross-market concentration effects involving biotech traits are statistically significant. This stresses the importance of a cross-market evaluation of market power. The *ECB* and *RW* cross-market effects (H_{23} and H_{32}) are both negative. This suggests that these two *IR* traits are complements to each other. Since these two traits are targeting the control of different insects, this could reflect the fact that crop damages caused by one insect infestation are larger in the presence of damages from another insect infestation. The *ECB* and *HT*1 effects (H_{24} and

H_{42}) are both positive, suggesting that the *ECB* and *HT*1 traits are substitutes. The *RW* and *HT*1 effects (H_{34} and H_{43}) are statistically significant but with opposite sign, suggesting that the *RW* trait and *HT*1 trait may have asymmetric effects on each other: *HT*1 trait is viewed as complement to *RW* trait by *RW* traited seed adopters; and *RW* trait is viewed as substitute for *HT*1 trait by *HT*1 traited seed adopters. This indicates that the effects of insect infestation on corn yield differ significantly from those for weed infestation.

Location effects: Corn seed prices are found to vary significantly across states. Compared to Illinois, the price difference is statistically significant for Iowa ($1.53), Indiana (-$1.13), Ohio (-$2.16), Wisconsin (-$2.34), and Kentucky (-$3.22). This suggests that seed companies do price discriminate across regions, reflecting spatial differences in elasticities of demand for seeds. The longitude variables are not statistically significant. But the latitude variables have significant effects on corn seed price: the linear term is positive while the quadratic term is negative. This suggests that seed price rises from south to north, reaches a peak near the center of the Corn Belt[19] and then declines when moving further north. This confirms significant differences in seed prices between the center of the Corn Belt and fringe regions.

Purchase source effects: Recall that most farmers purchase seed from "Farmer dealer or agent", followed by "Direct from seed company" , and "Myself, I am a dealer for that company" . Compared to purchasing from "Farmer dealer or agent", "buying directly from a seed company" costs about $4.57 less, while purchasing from "myself" costs about $4.40 less. These results may reflect the effect of farmer's bargaining position, but also possibly the presence of price discrimination across different modes of purchase.

[19] For the latitude, the peak is reached at 40.54, which is close to the center of our study region (mean latitude at 41.71)

Table 3. OLS and 2SLS regression with robust standard errors,[a, b, c, d]

Dependant Var: Price ($/bag)	OLS		2SLS	
	Coefficient	t-statistics	Coefficient	Robust z statistics
Characteristic effects, benchmark is K_1: Conventional seed				
K_2 (ECB)	24.31***	46.93	25.64***	12.65
K_3 (RW)	31.89***	23.82	46.06***	5.09
K_4 ($HT1$)	1.93***	2.97	-3.78	-1.16
K_5 ($HT2$)	6.92***	18.68	9.63***	10.28
K_{23}	-9.49***	-11.20	-11.20***	-7.06
K_{24}	-10.06***	-30.10	-13.83***	-13.75
K_{25}	-3.44***	-7.96	-5.82***	-6.00
K_{34}	-11.03***	-12.74	-14.35***	-10.13
K_{35}	0.39	0.33	-1.27	-0.67
K_{45}	-19.70**	-2.25	-21.95***	-2.92
K_{234}	-24.52***	-28.17	-30.62***	-11.82
K_{235}	-13.63***	-12.26	-18.71***	-6.47
K_{245}	-16.51***	-24.34	-22.92***	-11.84
K_{345}	-12.26***	-6.17	-17.36**	-5.98
K_{2345}	-28.85***	-24.78	-37.88***	-10.05
Market concentration effects				
H_{11} (conventional seed)	11.71***	15.83	14.81***	6.47
H_{22} (ECB)	1.45**	2.41	-0.57	-0.27
H_{33} (RW)	4.82**	2.04	32.00***	2.93
H_{44} ($HT1$)	11.25***	12.70	14.92***	2.91
H_{12} on conventional seed	28.06***	11.72	36.07***	3.10
H_{21} on ECB trait	-7.22***	-4.73	-7.29	-0.95
H_{13} on conventional seed/RW trait	-1.74	-1.00	2.78	0.21
H_{14} on conventional seed	-24.19***	-9.93	-14.58	-1.04
H_{41} on $HT1$ trait	9.22***	6.49	22.42*	1.78
H_{23} on ECB trait	-2.10***	-6.14	-3.42**	-2.38
H_{32} on RW trait	1.79	0.74	-28.87***	-3.45
H_{24} on ECB trait	-2.58***	-5.10	3.00*	1.66

H_{42} on $HT1$ trait	6.53***	9.59	10.07***	4.17
H_{34} on RW trait	-8.41***	-4.54	-24.98***	-2.98
H_{43} on $HT1$ trait	3.99***	9.35	7.77***	4.15
Other variables				
Post-exit1	-4.36*	-1.58	-2.77	-0.59
Pre-entry2	-5.50**	-2.21	-4.52	-1.21
Pre-entry3	-0.30	-1.34	0.12	-0.11
Pre-entry4	-7.75***	-3.64	-6.57**	-2.02
Total farm corn acreage (1000 acre)	0.75***	9.61	0.72***	4.68
Longitude	0.33***	2.90	0.37	1.49
Longitude squared	-0.01	-1.52	-0.01	-1.00
Latitude	0.97***	5.59	1.18***	3.30
Latitude squared	-0.11***	-6.93	-0.13***	-4.20
Year	2.30***	47.42	1.95***	13.95
Constant	71.01***	71.41	70.36***	29.39
Number of observations	123861			

[a] Statistical significance is noted by * at the 10 percent level, ** at the 5 percent level, ** at the 1 percent level.
[b] The R^2 is 0.54 for the OLS estimation. For the 2SLS estimation, the centered R^2 is 0.53, and un-centered R^2 is 0.98.
[c] Results for the location effects and purchase source effects are not reported here but are discussed in the text.
[d] The longitude and latitude measures are normalized by subtracting the lower bound (80 for longitude and 36 for the latitude) from the true value.

Other variables: Most exit and entry dummies are not statistically significant. The only exception is *Pre-entry4*, which is negative and statistically significant at the 5 percent level. The introduction of *HT*1 traited biotech seed may raise the price for all seeds, including the conventional ones. This result is consistent with the finding in Shi (2009), where she argues that the introduction of biotech seed can raise the conventional seed price. The farm size effect is statistically significant: large farms within each state pay more for corn seed. This result may be due to the fact that large farms are more productive (compared to smaller farms) and located in areas where corn hybrids are better tailored to local growing conditions. The time trend effect is positive and statistically significant, reflecting technological improvements in the seed industry.

Implications

In this section, our empirical estimates are used to generate insights on bundle pricing, and the interactive role of market power within and across markets on seed pricing. For illustration purpose, our analysis focuses on Illinois in 2004. Illinois is one of the largest corn-producing states in the US, and it has the largest number of farms in our sample. The year 2004 is chosen as it is in the middle of our sample period; and it avoids entry/exit events for traits.

Three sets of results are presented. First, we evaluate the effects of bundling/stacking by simulating how stacking influences seed prices. Second, we simulate the Lerner indexes applied to the pricing of different seed types. This provides useful information on the extent of departure from marginal cost pricing. Third, in a further evaluation of market power effects, we simulate the potential impact of merger activities.

Simulation of bundling effects

The bundling literature has identified situations where component pricing may not apply (e.g., when the demands for different components are correlated, or when consumers are heterogeneous in at least a subset of the component markets). As discussed above, our econometric results strongly reject component pricing (i.e., seeds being priced as the sum of their component values). This raises the question: how do prices vary across bundles? To address this question, we simulate the effects of bundling/stacking on seed prices using mean values of relevant variables for Illinois in 2004 (including farm size, the traditional HHIs (H_{ii}) and the cross market GHHIs (H_{ij})).[20]

[20] The purchase source is set to be from "Farmer who is a dealer or agent".

Table 4 contains the simulation results.[21] The simulated mean conventional seed price is \$90.86/bag, which is presented as the base case (case 1). Cases 2-16 involve biotech seeds, including stacked/bundled seeds. The last column of table 4 reports price premiums measured as price differences of each seed type compared to conventional seed. Except for the seed with two herbicide tolerant traits (case 11: K_{45}), all biotech seed price premiums are statistically different from the mean conventional seed at the 1 percent level or higher. Thus, seed companies are able to generate price premiums linked to specific biotech traits.

Cases 2-5 reflect the premium attached to seeds sold with a single biotech trait. Adding the *ECB* trait (K_2) alone raises the seed price by a premium of \$17.96. The corresponding price premium is \$29.91 for *RW* (K_3), \$13.03 for *HT*1 (K_4), and \$4.51 for *HT*2 (K_5).

Double, triple, and quadruple-stacked seed prices and premiums are presented in cases 6-15. Note first the \$41.74 premium for stacking *ECB* and *RW* traits (K_{23}). While this is greater than the price premium farmers pay for unstacked versions of these seeds (i.e., *K2* or *K3*), it is less than the sum of them (17.96 + 29.91 = \$47.87). A similar pattern is evident in all the double stacked seed prices except for case 10: K_{35} and case 11: K_{45}. The triple stacking of *ECB*, *RW* and *HT*1 traits (K_{234}) has a price premium of \$40.49. This is greater than the value of any individual trait component or any relevant double stacked seed price (except for K_{23} where the price difference is insignificant). But this is less than the sum of the individual premiums (\$65.41). Note also that adding the third trait to any of the K_{23}, K_{24}, or K_{34} seeds produces a marginal contribution of the third trait that is smaller than the contribution of the trait being added into a

[21] Note that we did not simulate the case for *HT*1 trait stacked with *HT*2 trait (K_{45}) because we have very few observations on the K_{45} stacking system. The same applies for K_{245}.

single traited system (to form a double stacking system) or alone (to form a single traited system). Other triple stacking systems follow a similar pattern. Finally, the price premium for quadruple stacking (K_{2345}) is $42.85, which is (weakly) greater than all other scenarios (including K_{235} and K_{345}). As before, the marginal contribution of each individual trait is again lower than in a triple system.

Table 4. Effects of Bundling/Stacking on Seed Prices, $/bag.[a]

Case	Traits	Expected Seed Price	Standard Error	Price difference from K_1 (Conventional)	Standard Error
1	K_1 (Conventional)	90.86***	0.46	0.00	
2	K_2 (*ECB*)	108.82***	0.49	17.96***	0.65
3	K_3 (*RW*)	120.78***	1.28	29.91***	1.16
4	K_4 (*HT*1)	103.89***	0.67	13.03***	0.79
5	K_5 (*HT*2)	95.38***	0.67	4.51***	0.80
6	K_{23}	132.60***	1.41	41.74***	1.34
7	K_{24}	113.13***	0.75	22.26***	0.88
8	K_{25}	112.62***	0.59	21.76***	0.72
9	K_{34}	124.54***	1.43	33.68***	1.33
10	K_{35}	129.11***	1.43	38.25***	1.56
11	K_{45}	91.40***	7.49	0.54	7.53
12	K_{234}	131.35***	1.42	40.49***	1.41
13	K_{235}	134.80***	1.64	43.94***	1.64
14	K_{245}	113.67***	0.90	22.81***	1.02
15	K_{345}	131.20***	2.19	40.34***	2.16
16	K_{2345}	133.72***	1.69	42.85***	1.74

[a] Statistical significance is noted by * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Overall, these results document significant departures from component pricing (where seeds are priced as the sum of their component values). The evidence supports sub-additive pricing. It shows that the marginal contribution of each component to the seed price declines with the number of components. Note that such a finding is consistent with the presence of economies of scope in seed production. Indeed, synergies in R&D investment (treated as fixed cost) across seed types can contribute to reducing total cost. This cost reduction can then be (at

least partially) shared with farmers in the form of lower seed prices. Our empirical evidence against component pricing and in support of sub-additive pricing could then be interpreted as indirect evidence of scope economies in seed production.

Estimated Lerner indexes

As discussed earlier, the Lerner index provides a simple characterization of the strength of imperfect competition: it is zero under marginal cost pricing, but positive when price exceeds marginal cost. The market power component M in equation (6) gives a per-unit measure of the price enhancement beyond marginal cost. And the associated Lerner index is $L = \frac{M}{p}$. Evaluated at sample means for Illinois in 2004, the Lerner indexes ($100 \times L$) are reported in Table 5 for selected seed types.

The Lerner indexes are statistically significant at the 10 percent level in four cases (out of eight cases).[22] When significant, the Lerner indexes are positive in three cases (conventional seed K_1, $HT1$ traited seed K_4, and double stacked seed of ECB and $HT1$ K_{24}) but negative in the case of K_{23} (double stacked seed of ECB and RW), with estimates of ($100 \times L$) varying from 5.92 percent for conventional seeds (K_1) to 20.87 percent for $HT1$ (K_4) for the positive cases and -10.11 percent for ECB and RW (K_{23}). This provides empirical evidence that market power affects seed prices. The effect of market power on price is found to be moderate in the conventional seed market K_1, but larger in the $HT1$ market. Finally, the Lerner indexes are not statistically different from zero for K_2 (ECB) and K_3 (RW), but is negative and statistically significant in the stacked market K_{23}. Thus, our analysis suggests empirical evidence of

[22] Cases involving the K_5 trait are dropped due to lack of variation in the K_5 market concentration.

complementarity interacting with market power: an increased market concentration in these two sub-market is associated with a price reduction in the relevant stacked seed market.

Table 5. Simulated Lerner Indexes[a]

	Lerner Index (100 × *L*)	Standard Error	t-ratio
K_1 (Conventional)	5.92***	1.51	3.91
K_2 (*ECB*)	-2.44	2.05	-1.19
K_3 (*RW*)	-8.99	6.31	-1.43
K_4 (*HT*1)	20.87***	2.79	7.47
K_{23}	-10.11**	5.02	-2.01
K_{24}	15.90***	2.89	5.50
K_{34}	8.47	6.72	1.26
K_{234}	6.00	5.64	1.06

[a] Lerner indexes are calculated from prices at the mean GHHI levels compared to the case of competition (GHHI=0)
[b] Statistical significance is noted by * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Effects of changing market structure

In equation (3), we defined the GHHI's $H_{ij} \equiv \sum_{n \in \mathbf{N}} s_i^n s_j^n$ for sub-markets *i* and *j*. As discussed above, the *H's* are endogenous variables measuring market concentrations. They provide useful information linking market structure with pricing. The assessment of changing market structures is complex in the presence of bundling when the same firms sell different bundled goods, as all the H_{ij}'s typically change in response to any change in industry structure. The changes in the H_{ij}'s depend on the nature of changes in firms' concentration in all relevant markets. This indicates that changes in market structure can have complex effects on prices.

We evaluated such effects by simulating the effects of changing market structures associated with alternative merger scenarios. Several simulations are presented to evaluate the potential effects of increased market concentrations on seed prices. Each simulation considers a hypothetical merger in a given market, merger leading to a monopoly in that market (where the

post-merger market share becomes equal to 1).[23] While these are rather extreme scenarios, the simulated effects can be interpreted as upper bound estimates of the potential impact of market power. Three sets of (hypothetical) mergers are simulated: 1/ mergers between biotech companies within each genetic trait market (*biotech/biotech within trait*); 2/ mergers between biotech companies producing different genetic traits (*biotech/biotech across traits*); and 3/ mergers between biotech companies and seed companies (*biotech/seed merger*). Again, such merger scenarios are counterfactual. They are presented to illustrate how our analysis can be used to evaluate the price implications of changing market structures.

The price effects of three sets of merger scenarios are reported in Table 6. The first set (scenarios 1-3) considers mergers between biotech companies within a given genetic trait market (*biotech/biotech within trait*). This covers mergers of biotech firms within the *ECB* market (scenario 1), within the *RW* market (scenario 2), and within the *HT*1 market (scenario 3). In scenarios 1-3, Table 6 shows that the effect of such mergers on seed price would not be statistically significant for *ECB* and *RW*. However, the effect is statistically significant for *HT*1. Our simulation results show that mergers of biotech firms in the *HT*1 markets could potentially induce a price increase of up to $19.08/bag of *HT*1 seed.

The second set (scenarios 4-6) considers mergers between biotech companies producing different genetic traits (*biotech/biotech across traits*). This covers mergers of biotech firms involved in *ECB* and *RW* markets (scenario 4), in *ECB* and *HT*1 markets (scenario 5), in *RW* and *HT*1 markets (scenario 6). In each case, the simulations again assume that the merger leads to a monopoly in the corresponding market (with a market share equal to 1). Table 6 shows that the mergers across *ECB* and *RW* markets are associated with a price reduction of $5.99/bag for *ECB*

[23] In situations where the mergers lead to increased market concentration but without full monopolization, note that our simulations present upper-bound estimates of the corresponding price effect.

seeds (scenario 4a), a price reduction of $25.10/bag for *RW* seeds (scenario 4b), and a price reduction of $31.09/bag for *ECB/RW* stacking seeds (scenario 4c). The results for scenario 4 underscore the importance of possible efficiency gains that might emerge from mergers. Mergers involving *ECB* and *HT*1 could potentially induce a price increase of up to $22.22/bag of *HT*1 seed (scenario 5b) and $22.55/bag of *ECB*/*HT*1 stacking seeds (scenario 5c), but not on the *ECB* trait market. And mergers involving *RW* and *HT*1 could be associated with a price reduction of up to $21.34/bag of *RW* seed (scenario 6a) and a price increase of up to $19.91/bag of *HT*1 seed (scenario 6b). However, the price effects on *RW*/*HT*1 stacking seeds (scenario 6c) are not statistically significant.

Finally, the third set (scenarios 7-9) considers mergers involving biotech companies and seed companies (*biotech/seed merger*). The simulations assume that the mergers lead to the monopolization in the corresponding biotech trait market. However, since the monopolization of seed companies is unlikely (there are too many seed companies), the mergers in scenarios 7-9 are assumed to increase market concentrations for conventional seed (as measured by the H_{ii}'s and H_{ij}'s) only to the maximum observed in our sample. How are mergers involving both seed companies and biotech firms associated with changes in conventional seed prices? The simulated price change can be up to +$32.37/bag when mergers involve *ECB* biotech firms (scenario 7). However, our simulations indicate that the effects of such mergers would not be statistically significant when it involves *RW* biotech firms (scenario 8) or when the mergers involve *HT*1 firms (scenario 9). Importantly, note that these simulation results capture cross-market effects contributing to the exercise of market power in the conventional seed market. These cross-market effects play a significant role in the evaluation of the exercise of market power.

Table 6. Simulated Merger Effects[a]

Sector affected by mergers	Scenarios	Market/Price Affected	Induced price change ($/bag)	Standard Error	t-ratio
ECB (K_2)	1	*ECB* (K_2)	-1.88	2.82	-0.67
RW (K_3)	2	*RW* (K_3)	-3.37	3.21	-1.05
*HT*1 (K_4)	3	*HT*1 (K_4)	19.08***	3.74	5.10
ECB and *RW* (K_2, K_3)	4a	*ECB* (K_2)	-5.99**	3.01	-1.99
	4b	*RW* (K_3)	-25.10***	9.35	-2.68
	4c	*ECB/RW* (K_{23})	-31.09***	10.45	-2.97
ECB and *HT*1 (K_2, K_4)	5a	*ECB* (K_2)	0.33	3.33	0.10
	5b	*HT*1 (K_4)	22.22***	4.52	4.92
	5c	*ECB*/*HT*1(K_{24})	22.55***	6.20	3.64
RW and *HT*1 (K_3, K_4)	6a	*RW* (K_3)	-21.34***	6.30	-3.39
	6b	*HT*1 (K_4)	19.91***	3.62	5.50
	6c	*RW*/*HT*1 (K_{34})	-1.43	6.14	-0.23
Conv. and *ECB* (K_1, K_2)	7	Conventional (K_1)	32.37***	8.93	3.62
Conv. and *RW* (K_1, K_3)	8	Conventional (K_1)	7.87	10.09	0.78
Conv. and *HT*1 (K_1, K_4)	9	Conventional (K_1)	-5.99	10.16	-0.59

[a] Statistical significance is noted by * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

The simulations in Table 6 illustrate the potential usefulness of the model in studying the effects of changing market concentrations. For example, in a pre-merger analysis, this would involve evaluating the HHIs and GHHIs in all relevant markets before and after a proposed merger with a quantitative assessment of the price effects. Alternatively, the model could be used to estimate the effects of spin-offs by evaluating their anticipated effects on HHIs and GHHIs and by simulating the associated price changes.

Concluding remarks

This paper has presented an analysis of bundle pricing under imperfect competition. A multiproduct Cournot model identifies the role of substitution/ complementarity in bundle pricing. It explains how oligopoly pricing manifests itself, and motivates generalized HHI measures of market concentration. The model is applied to the U.S. corn seed market and estimated using farm-level data from 2000-2007. The U.S. corn seed market represents a unique opportunity to evaluate the pricing of bundled goods, where patented genetic traits are inserted into conventionally bred corn seed either bundled or independently. These GM seeds compete alongside conventional seeds in a spatially diverse farm sector. There is considerable variation in the spatial concentration of conventional seeds and seeds with various patented genetic traits. Through the years of this study, GM seeds have been adopted quickly among U.S. farmers and are part of a broader wave of technological progress impacting the agriculture sector.

The econometric investigation documents the determinants of seed prices, including the effects of bundling and the pricing component associated with imperfect competition. Several major conclusions follow the research findings. First, we find extensive evidence of spatial price discrimination. We observe, *ceteris paribus*, that seed prices vary by state and in a south to north pricing pattern that peaks in the central part of the Corn Belt. This would be consistent with a type of price discrimination pattern that recognizes the inherent productivity of land in the Corn Belt. Second, we find strong evidence of subadditive bundle pricing, thus rejecting standard component pricing. This is consistent with the presence of economies of scope in seed production and/or demand complementarities. Third, we investigated the interactive role of market concentrations with complementarity/substitution effects in the pricing of seeds. Using generalized HHI's, this helps to document how traditional and cross-market effects of imperfect

competition can contribute to higher (or lower) seed prices. Our results indicate that Lerner indices for three seed types are positive and statistically significant while prices for one market indicate a pro-competitive environment. Fourth, our simulation of hypothetical mergers produced numerous interesting results. Perhaps most striking is a simulation involving a merger of conventional seed firm with a biotech firm selling seeds traited for ECB. Conventional seed prices provide an important competitive benchmark by which farmers can use to weigh the decision to purchase biotech seed. The simulated merger indicates that the conventional seed price would rise significantly. Such a price increase may be of great concern to policymakers because the impact would contribute to raising the price of the entire corn seed complex.

Our analysis could be extended in several directions. First, it would be useful to explore the implications of bundle pricing and imperfect competition in vertical markets. Second, there is a need for empirical investigations of bundle pricing analyzed jointly with bundling decisions. Third, it would be useful to estimate the separate effects of supply versus demand factors in bundle pricing. But this would require better data (especially on the supply side) to identify these effects separately. Finally, there is a need to explore empirically the economics of bundling applied to other sectors. These appear to be good topic for further research.

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