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

Guanming Shi, Jean-paul Chavas, and Kyle Stiegert

We investigate the pricing of traits in the U.S. corn seed market under imperfect competition. In a multiproduct context, we examine how substitution/complementarity relationships among products can affect pricing. This is used to motivate generalizations of the Herfindahl-Hirschman index capturing cross-market effects of imperfect competition on pricing. The model is applied to pricing of U.S. conventional and biotech seeds from 2000 to 2007. We reject the standard component pricing in biotech traits in favor of subadditive bundle pricing. The econometric estimates show how changes in market structure (as measured by both own- and cross-Herfindahl indexes) affect U.S. corn seed prices.

Key words: component pricing, imperfect competition, seed, biotechnology.

JEL codes: L13, L40, L65.

In the past 15 years, biotechnology has had a major impact on U.S. agriculture. Most notable has been the commercial development of genetically modified (GM) seeds for corn, cotton, and soybeans. GM seeds have contributed to agricultural productivity growth and exhibited rapid adoption among U.S. farmers (Fernandez-Cornejo 2004). GM traits involve patented technologies that offer specific on-board services to the plant, such as insect resistance and herbicide tolerance. The research and development (R&D) of seeds combining germplasms with GM traits has spawned increased product differentiation. GM seeds may carry either a single trait or combinations of several traits (often called stacked seed), sometimes patented by different biotech firms. GM seeds marketed to farmers are typically priced higher than conventional seeds, are often associated with modifications in farm production practices and carry legal restrictions related to the use or resale of patented seeds to others.

The structure of the seed markets involving GM traits has changed significantly over the last two decades (Fernandez-Cornejo 2004). While over 300 seed firms remain in the corn hybrid market, the four firm concentration ratio (CR4) in this market has risen above 70% since 2005.[1] GM corn accounted for about 80% of the total U.S. corn acreage in 2007. Of the GM corn acres planted in 2007, 56% involved seeds with two or more stacked traits.[2] Similar trends are present in cotton and soybeans. After a flurry of horizontal and vertical mergers in the 1990s, the corn seed industry is now dominated by six large biotech firms (Fernandez-Cornejo 2004),[3] four of which own subsidiary corn seed companies. 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. Such asset complementarities indicate that trait bundling may 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 rent from farmers. If so, increased market concentration can raise concerns about adverse effects of

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[1] The CR4 indexes (and the acreage statistics) are calculated from the survey data discussed below.

[2] Single-trait GM corn seeds were 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 2006.

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

Amer. J. Agr. Econ. 92(5): 1324–1338; doi: 10.1093/ajae/aaq063
Received October 2009; accepted May 2010; published online July 19, 2010

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.

The objective of the present paper is to evaluate the pricing of conventional and GM hybrid corn seeds under imperfect competition and product differentiation. We begin by developing a pricing model of differentiated products under a quantity-setting game. In a multiproduct context, we examine the linkages between pricing and substitution/complementarity relationships among products with different bundled characteristics. A multiproduct generalization of the Herfindahl-Hirschman index (hereafter GHHI) is then motivated, which captures cross-market effects of imperfect competition on bundle pricing. The GHHIs are then included in an econometric analysis of bundle pricing in the U.S. hybrid corn seed industry. To our knowledge, the present analysis is the first econometric investigation using GHHI to estimate the linkages between imperfect competition and multiproduct pricing. The model also allows for a test of standard component pricing for seeds with stacked GM traits. Applied to farm survey data, the econometric estimates provide useful information on the role of trait bundling and market structure in the pricing of U.S. hybrid corn seeds.

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 presented. Finally, we discuss the empirical findings and their implications.

The Model

Consider a market involving a set $\mathbf{N} = \{1, \ldots, N\}$ of N firms producing a set $\mathbf{T} = \{1, \ldots, T\}$ of T products. Denote by $\mathbf{y}^n \equiv (y_1^n, \ldots, y_m^n, \ldots, y_T^n) \in \Re_+^T$ the vector of output quantities produced by the nth firm, y_m^n being the mth output quantity produced by the nth firm, $m \in \mathbf{T}, n \in \mathbf{N}$. The price-dependent demand for the mth product is $p_m(\sum_{n\in\mathbf{N}} \mathbf{y}^n)$. The profit of the nth firm is $\pi^n = \sum_{m\in\mathbf{T}}[p_m(\sum_{n\in\mathbf{N}} \mathbf{y}^n) y_m^n] - C_n(\mathbf{y}^n)$, where $C_n(\mathbf{y}^n)$ denotes the nth firm's cost of producing $\mathbf{y}^n$. Assuming a Cournot game and under differentiability, the nth firm's profit maximizing decision $\mathbf{y}^n$ must satisfy $\pi^n \geq 0$ and the Kuhn-Tucker conditions:

$$(1a) \quad p_m + \sum_{k\in\mathbf{T}} \frac{\partial p_k}{\partial y_m^n} y_k^n - \frac{\partial C_n}{\partial y_m^n} \leq 0$$

$$(1b) \quad y_m^n \geq 0$$

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

Equation (1*c*) is the complementary slackness condition. It applies whether the mth product is produced by the nth firm ($y_m^n > 0$) or not ($y_m^n = 0$). Equation (1*c*) is important for our analysis: it remains valid irrespective of the firm entry/exit decision in the industry. And equation (1*c*) holds no matter how many of the T products the firm chooses to sell.

Below, we consider the case of linear demands, $p_k = \alpha_k + \sum_{m\in\mathbf{T}}(\alpha_{km} \sum_{n\in\mathbf{N}} y_m^n)$, with $\frac{\partial p_k}{\partial y_m^n} = \alpha_{km}$ and $\alpha_{mm} < 0$, k, $m \in \mathbf{T}$. We also assume that the cost function takes the form $C_n(\mathbf{y}^n) = F_n(\mathbf{S}^n) + \sum_{m\in\mathbf{T}} c_m y_m^n$, where $\mathbf{S}^n = \{j \in \mathbf{T} : y_j^n > 0\}$ is the set of products produced at positive levels by the nth firm. Here, $F_n(\mathbf{S}^n) \geq 0$ denotes fixed cost that satisfies $F_n(\emptyset) = 0$. Such fixed cost may include R&D expenditure, distribution channel costs, federal registration fees, and other relevant marketing costs. And the term c_m denotes constant marginal cost of producing the mth output. Note that the presence of fixed cost (where $F_n(\mathbf{S}^n) > 0$ for $\mathbf{S}^n \neq \emptyset$) implies increasing returns to scale. With positive fixed cost, marginal cost pricing would imply negative profit ($\pi^n < 0$) for any $\mathbf{y}^n \neq 0$, corresponding to prices not high enough to cover the fixed cost $F_n(\mathbf{S}^n) > 0$. Therefore, any sustainable equilibrium must be associated with departures from marginal cost pricing. Fixed cost can also reflect the presence of economies of scope, which would occur when $F_n(\mathbf{S}_a^n) + F_n(\mathbf{S}_b^n) > F_n(\mathbf{S}_a^n \cup \mathbf{S}_b^n)$ for some $\mathbf{S}_a^n$, $\mathbf{S}_b^n \subset \mathbf{T}$, i.e., when the joint production of outputs in $(\mathbf{S}_a^n \cup \mathbf{S}_b^n)$ reduces fixed cost (Baumol, Panzar, and Willig 1982, p. 75). A relevant example is R&D investment as a fixed cost contributing to the joint production of outputs in $(\mathbf{S}_a^n \cup \mathbf{S}_b^n)$. Indeed, because of synergies in R&D across biotech traits, a biotech firm could reduce its aggregate fixed R&D investment by working on the joint development of several traits (compared with traits being produced by specialized firms). In the case of joint development of traits, scope economies could come from cost savings obtained from sharing knowledge and laboratory equipment and reducing management cost of the research team. Alternatively, diseconomies of scope could develop in situations where managing multi-output processes increase fixed cost. Examples include increased setup costs and excessive administrative burdens.

Our analysis exploits the information presented in equation (1*c*).[4] Let $Y_m = \sum_{n \in \mathbf{N}} y_m^n > 0$ denote the aggregate output of the *m*th product. 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. Similarly, let $s_k^n = \frac{y_k^n}{Y_k} \in [0, 1]$ be the market share of the *n*th firm for the *k*th product, with $Y_k = \sum_{n \in \mathbf{N}} y_k^n > 0$ denoting the aggregate output of the *k*th product. Dividing equation (1*c*) by Y_m and summing across all $n \in \mathbf{N}$ yields

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

where c_m is the marginal cost of the *m*th output, and $\alpha_{km} = \frac{\partial p_k}{\partial y_m^n}$ is the slope of the demand curve measuring the marginal impact of the *m*th quantity demanded on the *k*th price. Note that equation (2) applies for any arbitrary number of products in the product space **T**. It includes own-market effects when $k = m$, and it captures pairwise cross-market effects when $m \neq k$.

Equation (2) can be alternatively written as

$$(3) \qquad p_m = c_m - \sum_{k \in \mathbf{T}} \alpha_{km} H_{km} Y_k$$

where $H_{km} \equiv \sum_{n \in \mathbf{N}} s_k^n s_m^n$.

Equation (3) is a price-dependent supply function 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} values are endogenous (as they are both influenced by firms' strategies). Thus, equation (3) provides useful linkages between price and market structure. With c_m being marginal cost, equation (3) shows that any departure from marginal cost pricing can be measured as

$$(4) \qquad M_m = - \sum_{k \in \mathbf{T}} \alpha_{km} H_{km} Y_k.$$

The Lerner index is defined as $L_m = \frac{p_m - c_m}{p_m}$. It 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.[5] 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 $L_m = \frac{M_m}{p_m} = \frac{M_m}{c_m + M_m}$. Thus M_m in equation (4) gives a measurement 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 a single active firm operating across all markets). In other words, the term M_m in equation (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 own-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).[6]

Equation (3) extends the HHI to a multiproduct context. It defines H_{km} as a GHHI. When $k \neq m$, it shows that a rise in the "cross-market" GHHI H_{km} would be associated with

[4] Note that under Cournot behavior, equation (3) is a necessary but not sufficient condition for profit maximization by the *n*th firm. For example, equation (3) does not include the role of fixed cost $F_n(\mathbf{S}^n)$, which affects the nonnegative profit condition $\pi^n \geq 0$. To the extent that fixed cost can generate economies of scope (as discussed above), it means that equation (3) cannot reveal direct information on economies of scope. However, indirect information about economies of scope can still be obtained, as scope benefits would affect the observed prices and market share of each firm (through the profit condition $\pi^n \geq 0$).

[5] As pointed out by an anonymous reviewer, the Lerner index captures information about only the difference between price and marginal cost. It therefore neglects information about fixed cost and its effect on firm profit.

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

an increase (a decrease) in the Lerner index L_m and in the price p_m if $\alpha_{km} < 0$ (> 0). This shows how 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 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. It follows that the terms $\{H_{km} : k \neq m\}$ in equations (3) and (4) capture the role of substitution or complementarity among products (through the terms α_{km}) and the effects of cross-market concentration on the Lerner index and prices. Indeed, 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).

Previous research has pointed out the complex linkages between bundling strategies and the exercise of market power in bundling (e.g., Adams and Yellen 1976; McAfee, McMillan, and Whinston 1989; Venkatesh and Kamakura 2003; Fang and Norman 2006). Equation (3) captures the essence of bundle pricing under imperfect competition in a multiproduct framework. On the supply side, to be sustainable, prices given in equation (3) must generate nonnegative profit for each firm, $\pi^n \geq 0$. As noted above, fixed cost may imply economies of scope when $F_n(\mathbf{S}_a^n) + F_n(\mathbf{S}_b^n) > F_n(\mathbf{S}_a^n \cup \mathbf{S}_b^n)$. It means that a firm can lower its (fixed) cost by selling multiple products, which may allow it to charge lower prices without making losses. In this case, economies of scope may contribute to discount bundle pricing. On the demand side, equation (3) shows how the HHI and GHHIs capture the effects of market power on bundle pricing. In particular, for $m \neq k$, the GHHIs capture the effects of complementarity or substitutability across products. Equation (3) will be used below in our empirical investigation of pricing in the U.S. hybrid corn seed market.

The U.S. Corn Seed Market

Our analysis relies on a large dataset providing detailed information on the U.S. corn seed market. The data were collected by dmrkynetec (hereafter dmrk)[7] using computer assisted telephone interviews. The dmrk data come from a stratified sample of U.S. corn farmers surveyed annually from 2000 to 2007.[8] The surveys provide farm-level information on corn seed purchases, corn acreage, seed types, and seed prices. About 40% to 50% of the farms surveyed each year remain in the sample for the next year. The dmrk data contain 168,862 transactions from 279 USDA crop-reporting districts (CRDs). A total of 38,617 farms were surveyed during 2000–2007, with each farm purchasing on average four to five different corn seed types each year. Our analysis considers only transactions in CRDs in the Midwest with more than ten farms sampled each year. In total, our data contain 139,410 observations from 80 CRDs in 12 states.[9]

There are two major groups of genes/traits in GM corn seeds: insecticide resistance and herbicide tolerance. The insect resistance traits focus on controlling damages caused by the European corn borer (*ECB*), and rootworms (*RW*).[10] The herbicide tolerance technology provides farmers with on-board early plant protection from applying formula-specific (i.e., branded) herbicides. Insect resistance reduces yield damages caused by insects and reduces or eliminates pesticide applications. Herbicide tolerance helps reduce yield reductions from competing plants (weeds) and allows for greater flexibility in making spring planting decisions. Figure 1 shows the evolution of corn acreage shares reflecting adoption rates of conventional and GM hybrid corn seed in the United States from 2000 to 2007 using the dmrk data. The acreage share of conventional seeds decreased rapidly: from 67.5% in 2000 to 20.6% in 2007. Table 1 presents the average price of different hybrid corn seeds ($ per bag) in our sample. The presence of a biotech trait tends to add value to the conventional germplasm, and multiple trait-stacking or bundling is typically worth more than single-trait seeds. Note that, being at the national level, the information presented in figure 1 and table 1 masks important spatial market differences. For example, in spite of a rapid adoption of biotech seeds, the dmrk data show that conventional seeds

[7] The firm dmrkynetec changed its name to GfK Kynetec in May 2009, web address: www.gfk.com. The seed data set is one of their products, called TraitTrak.

[8] The survey is stratified to oversample large corn producers. The sampling weights are constructed using farm census data.

[9] They are: Illinois, Indiana, Iowa, Kansas, Kentucky, Michigan, Minnesota, Missouri, Nebraska, Ohio, South Dakota, and Wisconsin.

[10] Yield loss due to *ECB* or *RW* has been estimated for each to average about 5% with wide variability over time and space (Hyde et al. 1999; Payne, Fernandez-Cornejo, and Daberkow 2003).

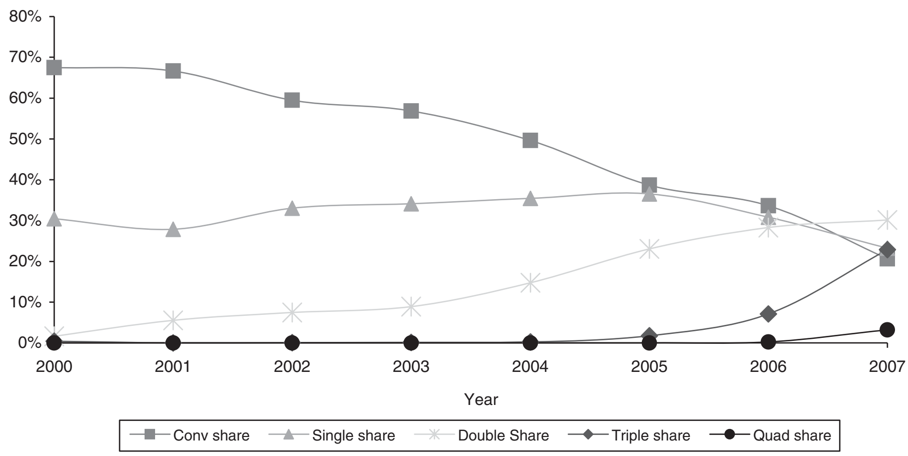

Figure 1. Percentage of U.S. acreage planted in conventional and GM corn seed, 2000–2007

Table 1. Average Nominal Price for Different Seeds ($ per bag), 2000–2007

Year	Conv.	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

still dominate in some local markets. This indicates the presence of spatial heterogeneity in the U.S. corn seed market. As discussed below, such heterogeneity also applies to seed prices.

Econometric Specification

Our analysis of corn seed prices builds on equation (3), which, as derived, is a structural equation reflecting the determinants of pricing in a multiproduct quantity-setting game.[11] As discussed in the model section, cost can affect bundle pricing. Also, the effects of imperfect competition on price were shown to depend on the nature of substitution/complementarity across traits. Below, we specify a modified version of equation (3) that reflects the effects of both bundling and market structure on corn seed prices.

Consider 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 ith characteristics, $i = 1, \ldots, J$. In our analysis, we consider $J = 5$. Conventional seeds are denoted by $K_1 = 1$, while $\{K_2, \ldots, K_5\}$ correspond to the GM traits in corn seeds. The GM seeds include two insect resistance traits, to European corn borer *ECB* ($K_2 = 1$) and to root worm *RW* ($K_3 = 1$); and two herbicide tolerance traits, $HT1$ ($K_4 = 1$) and $HT2$ ($K_5 = 1$).[12] Single-trait GM seeds include only one GM trait. But bundled/stacked GM seeds include more than one GM trait. We let $K_i = 1$ if a GM seed includes the ith GM trait (either individually or stacked), and $K_i = 0$ otherwise. In the absence of bundling/stacking,

[11] The use of a quantity-setting assumption is motivated in two ways. First, due to time lags in the production of seeds, the quantity of each seed type is determined in the previous growing year: seed firms contract with farmers to produce conventional and GM hybrids. Second, price games under a capacity constraint map to quantity-setting outcomes (Kreps and Scheinkman 1983).

[12] In our data, we observe that farmers purchase seeds inserted with both herbicide tolerance traits, implying that farmers see $HT1$ and $HT2$ as being differentiated.

K satisfies $\sum_{i=1}^{J} K_i = 1$. However, in the presence of stacking, biotech seeds 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).[13] Consider the hedonic equation representing the determinants of the price p for a seed of characteristics $\{K_1, K_2, \ldots, K_5\}$:

$$(5a)\quad p = \beta + \sum_{i=1}^{5} \delta_i K_i + \sum_{j=i+1}^{5} \sum_{i=2}^{5} \delta_{ij} K_{ij} + \sum_{z=j+1}^{5} \sum_{j=i+1}^{5} \sum_{i=2}^{5} \delta_{ijz} K_{ijz} + \sum_{r=z+1}^{5} \sum_{z=j+1}^{5} \times \sum_{j=i+1}^{5} \sum_{i=2}^{5} \delta_{ijzr} K_{ijzr} + \boldsymbol{\phi}\mathbf{X} + \varepsilon$$

where $\mathbf{X}$ 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 ith and jth GM traits. Similarly, K_{ijz} and K_{ijzr} are dummy variables representing triple-stacking and quadruple-stacking, respectively.[14]

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 equation (5a) capture the supply-side effects of bundling on seed price. The dmrk data reveal that trait bundling is common, which allows us to test for its price impact. 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 ith genetic material). When the parameters δ_{ij}, δ_{ijz}, and δ_{ijzr} are not all zero, equation (5a) allows for nonlinear pricing associated with bundled goods under stacking.

The parameters δ_{ij}, δ_{ijz}, and δ_{ijzr} can be either negative or positive. When negative, these parameters would reflect sub-additive bundle pricing. The price of the bundle would then be "discounted" compared to component pricing. 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. Alternatively, positive parameters would correspond to super-additive bundle pricing.

Next, we introduce market structure effects in equation (5a) by specifying

$$(5b)\quad \delta_i = d_{0i} + d_{ii} H_{ii}$$

where, for each CRD, $H_{ii} \equiv \sum_{n \in \mathbf{N}} s_i^n s_i^n$ is the traditional HHI, in which s_i^n represents the market share of the nth firm in the market for the ith characteristics. We construct the market share using trait acreage. Thus in the GM trait market, only a few biotech firms owning the patent of each trait are involved. The market share of each company's trait is constructed as the firm-specific trait acreage divided by the total trait acreage in the local market. In the conventional seed market, many more seed companies are involved, and the market share is constructed as the firm-specific conventional seed acreage divided by total conventional seed acreage in the local market.

We further specify

$$(5c)\quad \beta = \beta_0 + \sum_{j=i+1}^{5} \sum_{i=1}^{5} \beta_{ij} H_{ij} K_i + \sum_{j=i+1}^{5} \sum_{i=1}^{5} \beta_{ji} H_{ji} K_j$$

where $H_{ij} \equiv H_{ji} \equiv \sum_{n \in \mathbf{N}} s_i^n s_j^n$ is the cross-market GHHI that measures concentration for firms operating in the market for both ith and jth characteristics. With this specification, the coefficients on the GHHI terms capture the net effects associated with efficiency gains, market power, and other possible strategic considerations across different product types. Since the HHI and the GHHIs are zero under

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

[14] Note that K in equation (5a) satisfies $\sum K_i - \sum\sum K_{ij} - 2\sum\sum\sum K_{ijz} - 3\sum\sum\sum\sum K_{ijzr} = 1$, because the trait dummy variable K is double-counted once in the double-stacking dummies, twice in the triple-stacking dummies, and three times in the quadruple-stacking dummies. This equality implies that these dummy variables are perfectly collinear with the intercept. To deal with this issue below, we set $\delta_1 = 0$ in equation (5a), meaning that the intercept reflects the price of conventional seeds and that the other δ parameters measure price differences relative to conventional seeds.

competitive conditions, it follows from equations (4) and (5*a*)–(5*c*) that the market power component of the price of seed with the *i*th characteristics is given by

$$M_i = d_{ii}H_{ii}K_i + \sum_{j=i+1}^{5}\sum_{i=1}^{5}\beta_{ij}H_{ij}K_i. \tag{6}$$

In a way similar to equation (4), equation (6) provides a representation of the linkages among market structure, imperfect competition, and pricing. As noted in the model section, the term M_i in equation (6) measures the difference between price and marginal cost. It can be used to obtain the associated Lerner index $L_i = \frac{M_i}{p_i}$.

Our model specification allows us to estimate the pricing of each seed type along with stacking effects. To illustrate, from equations (5*a*)–(5*c*), for a double-stacked seed with *ECB* and *HT*1 ($K_2 = 1, K_4 = 1$, and $K_{24} = 1$), the price equation is

$$\begin{aligned} p_{24} = {} & \beta_0 + \delta_{02} + \delta_{04} + \delta_{24} + d_{22}H_{22} \\ & + d_{44}H_{44} + \beta_{21}H_{21} + \sum_{j=3}^{5}\beta_{2j}H_{2j} \\ & + \sum_{i=1}^{3}\beta_{4i}H_{4i} + \beta_{45}H_{45} + \boldsymbol{\phi}\mathbf{X} + \varepsilon. \end{aligned} \tag{7}$$

Equation (7) shows how traits, stacking, and market concentration are associated with pricing. Specifically, the δ_{02} and δ_{04} terms measure the component value of each respective trait, and δ_{24} measures the marginal impact of stacking *ECB* and *HT*1 in a single GM seed. The d_{ii} terms capture own-market concentration effects (measured by HHI), and β captures cross-market concentration effects (measured by the GHHIs).

The relevant covariates in **X** include a time trend, each farm's total corn acreage, binary terms that control for the source of each transaction, and a set of location variables. The time trend is included to capture advances in hybrid and genetic technology and other time-related factors such as structural changes taking place during the study years. Farm acreage captures possible price impacts associated with farm size (including productivity differences and/or volume discounts that could vary with farm size). Although the surveys defined 16 possible purchasing sources, over 80% of the transactions were classified into three categories: "Farmer who is a dealer or agent" (33.1%); "Direct from seed company or their representatives" (29%); and "Myself, I am a dealer for that company" (16.1%). The source of purchase can capture possible price differences linked to alternative marketing strategies.

Spatial effects enter our model via state dummy variables along with linear and quadratic terms for the longitude and latitude of the county. Since the inception of the hybrid corn seed technology in the 1930s, new hybrids have been developed and marketed to farms on a regional basis (Griliches 1960). The advent of GM seeds has not changed the need for seeds to perform well under specific growing conditions that can vary across regions. Our location variables are designed to control for possible pricing differences associated with spatial heterogeneity in farming systems (e.g., differing crop rotations) and agro-climatic conditions (soil quality, length of the growing season, rainfall patterns, etc.).

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 in equation (5*a*). 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 for the K_1 market; *Pre-entry*2 = 1 for the K_2 market; *Pre-entry*3 = 1 for the K_3 market; and *Pre-entry*4 = 1 for the K_4 market.[15]

Estimation

Table 2 reports summary statistics of key variables used in the analysis. Each CRD is presumed to represent the relevant market area for each transaction; thus, all *H* terms are calculated at that level. We report the sample mean of the H_{ii} and H_{ij} across all CRDs for each seed type. While the average of HHI shows that the conventional seed markets appear concentrated (with $H_{11} = 0.242$, which is above the

[15] 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.

Table 2. Summary Statistics

Variable	Number of Observations	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

Note: The data contain 139,410 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. For the market concentration measurement H values, we report the summary statistics of only those nonzeros at the CRD level; therefore, the number of observations is at most $80 \times 8 = 640$.

Department of Justice's threshold of 0.18 for identifying "significant market power"), they are not as concentrated as the biotech trait markets. The average HHI for the three biotech trait markets is over 0.80.

One econometric issue in the specification in equations (5*a*)–(5*c*) is the endogeneity of H. Market concentrations (as measured by H) and seed pricing are expected to be jointly determined, as they both depend on firm strategies. For example, if a major seed firm uses a strategy focusing on increasing farmers' adoption, it may price the seed lower. The low price may increase the firm's market share and result in higher H (for both HHI and GHHIs). To the extent that parts of the determinants of these strategies are unobserved by the econometrician, this would imply that H is correlated with the error term in equation (5*a*). In such situations, least-squares estimation of equations (5*a*)–(5*c*) would yield biased and inconsistent parameter estimates (due to endogeneity bias). To address this issue, we first test for possible endogeneity of H using a C statistic calculated as the difference of two Sargan statistics (Hayashi 2000, p. 232). The test is robust to violations of the conditional homoscedasticity assumption (Hayashi 2000, p. 232).[16] In our case, the C statistic is 200.16, showing strong statistical evidence against the null hypothesis of exogeneity of H.

To correct for endogeneity bias, equations (5*a*)–(5*c*) are estimated by an instrumental variable (IV) estimator. We used as instruments the lagged values of each H and the lagged market size for each seed type. These lagged variables are good candidates for instruments: given the time lag required to produce seeds, they are part of the information available to firm managers at the time seed quantity decisions are made. We investigated the statistical validity of these instruments. The Hansen overidentification test is not statistically significant, indicating that our instruments appear to satisfy the required orthogonality conditions. On that basis, equations (5*a*)–(5*c*) was estimated by two-stage least squares (2SLS).

A second test was used to evaluate the presence of unobserved heterogeneity across farms. A Pagan-Hall test[17] found strong evidence against homoscedasticity of the error term in equation (5*a*). As reported earlier, each farm purchases on average four to five different seeds. Some large farms actually purchase up to thirty 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 the variance of the error term in equation (5*a*) exhibits heteroscedasticity. On that basis, we relied on heteroscedastic-robust

[16] Under conditional homoscedasticity, the C statistic is numerically equivalent to a Hausman test statistic.

[17] Compared with 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).

standard errors with clustering at the farm level in estimating equations (5*a*)–(5*c*).

Additional tests of the validity of the instruments were conducted. In the presence of heteroscedastic errors, we used the measures by Bound, Jaeger, and Baker (1995) 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., well above ten). Following Staiger and Stock (1997), this means that there is no statistical evidence that our instruments are weak. Finally, we conducted the Kleibergen-Paap weak instrument test (Kleibergen and Paap 2006).[18] The test statistic is 5.81. Using the critical values presented in Stock and Yogo (2005), this indicated that our analysis does not suffer from weak instruments.

Empirical Results

Equations (5*a*)–(5*c*) are estimated using 2SLS, with heteroscedastic-robust standard errors under clustering at the farm level. We first tested whether the cross-market GHHI impact is symmetric: $H_0 : \beta_{ij} = \beta_{ji}$, where β terms are the coefficients of the corresponding GHHIs. 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 purpose of comparison, the ordinary least squares (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 the associated bias of the OLS estimation). Our discussion below focuses on the 2SLS estimates. We first discuss the price impacts associated with introducing single biotech traits. This builds toward a broader assessment of the impacts of bundling/stacking of traits and of the role of market power. These effects are further investigated below.

Characteristic effects

The coefficients of the terms K_2 (ECB), K_3 (RW), and K_5 ($HT2$) show statistically significant price premiums of \$25.64, \$46.06, and \$9.63 per bag, respectively, over the price of conventional seed. The coefficient of K_4 ($HT1$) is negative but insignificant.

The coefficients of the terms K_{ij}, K_{ijz}, and K_{ijzr} provide useful information on the effects of trait bundling/stacking 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 specification section, component pricing is associated with the null hypothesis that all stacking coefficients are zero. Using a Wald test, the null hypothesis that the stacking coefficients 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 potential prevalence of subadditive pricing of corn seed in their individual components. However, an overall evaluation of the bundling effects also requires including the market concentration effects. Such an evaluation is presented below.

Market concentration effects

The price effects of changes in the traditional Herfindahl indexes for each seed type are presented in the first four rows of the "Market concentration effects" in table 3.[19] 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 (H_{33}) and the $HT1$ trait market (H_{44}) was 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 ($HT1$) seeds. Finally, the concentration effect in the ECB trait market (H_{22}) is negative but not statistically significant.

We have argued 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

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

[19] We do not observe nonzero H_{15} because no firm that operates in the $HT2$ market sells a conventional seed. Similar situations arise for H_{25}, H_{35}, and H_{45}. Finally, note that $H_{55} = 1$ because only one firm operates in this trait market.

Table 3. OLS and 2SLS Regression with Robust Standard Errors

	OLS		2SLS	
Dependent Var: Price ($/bag)	Coefficient	*t*-Statistic	Coefficient	Robust z-Statistic
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 *HT*1 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 *HT*1 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 *HT*1 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 (1,000 acres)	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		123,861		

Note: Statistical significance is noted by an asterisk (*) at the 10% level, two asterisks (**) at the 5% level, and three asterisks (***) at the 1% level. The R^2 is 0.54 for the OLS estimation. For the 2SLS estimation, the centered R^2 is 0.53, and the uncentered R^2 is 0.98. Results for the location and purchase source effects are not reported here but are discussed in the text. The longitude and latitude measures are normalized by subtracting the lower bound (80 for longitude and 36 for latitude) from the true value.

be associated with a rise (decrease) in the price if the two components are substitutes (complements).

Of the five GHHIs that involve conventional seeds (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 that 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 GM trait and conventional seed.

All the cross-market concentration effects involving biotech traits are statistically significant. This is a major finding that stresses the importance of the general market structure in a multiproduct setting. The *ECB* and *RW* cross-market effects (H_{23} and H_{32}) are both negative, suggesting that insect resistance traits are complements to each other. A plausible explanation may be that crop damages caused by one insect infestation are larger in the presence of damages from other insects. 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: the *HT*1 trait is viewed as a complement to the *RW* trait by *RW* traited seed adopters; and the *RW* trait is viewed as a substitute for the *HT*1 trait by *HT*1 traited seed adopters. This suggests 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 with Illinois, the price difference is statistically significant for Iowa ($1.53), Indiana (−$1.13), Ohio (−$2.16), Wisconsin (−$2.34), and Kentucky (−$3.22). It appears that seed companies are able to price-discriminate across regions, reflecting spatial differences in farmers' willingness-to-pay and demand elasticities. 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. Seed price rises from south to north, reaches a peak near the center of the Corn Belt,[20] and then declines when moving farther north. This confirms significant differences in seed prices between the center of the Corn Belt and fringe regions.

Other variables. Except for *Pre-entry4,* which represents the entry of *HT*1 into specific markets, all other exit and entry dummies are statistically insignificant. The negative sign on the *Pre-entry4* variable indicates that 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 by Shi (2009), who 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.[21] The time trend effect is positive and statistically significant, possibly capturing the effect of inflation.

Finally, we found statistically significant differences in pricing across seed purchase sources. Compared with purchasing from "Farmer who is a dealer or agent," buying "Direct from seed company or their representatives" cost about $4.57 less, while purchasing from "Myself, I am a dealer for that company" cost about $4.40 less. These results may reflect the effect of farmers' bargaining position, but also possibly the presence of price discrimination across different modes of purchase.

Implications

In this section, our empirical estimates are used to generate additional insights on bundle pricing and the interactive role of market structure within and across markets on seed pricing. Our analysis focuses on Illinois, which is one of the largest corn-producing states in the United States. 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 avoids entry/exit events for traits. In each

[20] For the latitude, the peak is reached at 40.54. Note that the mean latitude of our study region is 41.71.

[21] This suggests that larger farms may be relatively more productive (compared with smaller farms) and thus may have a higher willingness to pay for seeds. Note that this result is conditional on a particular purchase source. Note that, as pointed by the editor, larger farms are also more likely to be dealers (who tend to face lower prices, as discussed below).

Table 4. Simulated Lerner Indexes

	Lerner Index (100 × *L*)	Standard Error	*t*-Ratio
Conventional	5.92***	1.51	3.91
ECB single	−2.44	2.05	−1.19
RW single	−8.99	6.31	−1.43
*HT*1 single	20.87***	2.79	7.47
ECB/RW double	−10.11**	5.02	−2.01
*ECB/HT*1 double	15.90***	2.89	5.50
*RW/HT*1 double	8.47	6.72	1.26
*ECB/RW/HT*1 triple	6.00	5.64	1.06

Note: Lerner indexes are calculated from prices at the mean GHHI levels compared with the case of competition (GHHI = 0). Statistical significance is noted by an asterisk (*) at the 10% level, two asterisks (**) at the 5% level, and three asterisks (***) at the 1% level.

of our exercises, bootstrapped standard errors are obtained to support hypothesis testing.

Bundling

For the first simulation, we evaluated the effects of bundling/stacking on seed prices. The bundling literature has identified situations where component pricing may not apply (e.g., when the demands for different components are correlated, when consumers are heterogeneous in at least a subset of the component markets). As discussed above, an overall evaluation of the bundling effects needs to combine both supply-side and demand-side effects. Our econometric results strongly reject component pricing on the supply side while finding some statistical evidence suggesting both complementarity and substitutability in demand (implying the possibility of observing either subadditive or superadditive pricing). The simulation results (available upon request) suggest that in general, traited seeds generated statistically significant premiums over conventional seeds, with strong statistical evidence of subadditive pricing in bundling two, three, and four traits. Subadditive pricing may be driven by price discrimination associated with imperfect competition and complementarity in demand or the presence of scope economies in the production of bundled/stacked seeds, or both. As discussed above, scope economies would be consistent with synergies in R&D investment (treated as fixed cost) across stacked seeds. The subadditivity of prices encourages more rapid farm adoption of stacked seeds.

Estimated Lerner indexes

Second, we simulate the Lerner indexes applied to the pricing of different seed types. 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_i in equation (6) gives a measure of price enhancement beyond marginal cost. And the associated Lerner index, expressed as a percentage term, is $100 \times \frac{M_i}{p_i}$. Evaluated at sample means for Illinois in 2004, the Lerner indexes are reported in table 4 for selected seed types.

The Lerner indexes are statistically significant at the 5% level in four of eight cases.[22] The significant Lerner indexes are positive in three cases: conventional seed (5.92%), *HT*1 traited seed (20.87%), and double-stacked seed of *ECB* and *HT*1 (15.9%); and negative in the case of double-stacked seed of *ECB* and *RW* (−10.11%). The results provide empirical evidence that market structure affects seed prices. The effect of market power on price is found to be smallest in the conventional seed market but large in the *HT*1 seed market and the *ECB/HT1* bundled seed market. While the Lerner indexes are not statistically different from zero for single trait *ECB* and *RW* seed markets, they exhibit a negative and statistically significant price effect in the stacked market *ECB/RW*. Thus, our analysis shows empirical evidence of complementarities interacting with market structure: an increased market concentration in these two submarkets is associated with a price reduction in the relevant stacked seed market.

Market structure

In our conceptual framework, we develop the GHHIs ($H_{ij} \equiv \sum_{n \in \mathbf{N}} s_i^n s_j^n$ for submarkets i and j) as a way to link market structure with pricing

[22] Cases involving the *HT*2 trait are dropped due to lack of variation in the *HT*2 market concentration.

in a multiproduct framework. When market shares of different products change, several GHHIs also change. Thus, the assessment of changing market structures is complex in the presence of bundling. To evaluate such issues, we simulated 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 leading to a monopoly for a given GM trait market. 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: (*a*) mergers between biotech companies within each GM trait market (*biotech/biotech within trait*); (*b*) mergers between biotech companies producing different GM traits (*biotech/biotech across traits*); and (*c*) mergers between biotech companies and traditional independent seed companies (*biotech/seed merger*). Each merger scenario is counterfactual and is used to illustrate how our analysis can evaluate the price implications of changing market structures.

The price effects of three sets of merger scenarios are reported in table 5. The first set (scenarios 1–3) considers mergers of biotech firms within the *ECB* market (scenario 1), within the *RW* market (scenario 2), and within the *HT*1 market (scenario 3). As shown in table 5, the effect of such mergers on seed price would not be statistically significant for *ECB* and *RW*, but would be for *HT*1. Our simulation results show that mergers of biotech firms in the *HT*1 markets could 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. This covers mergers of biotech firms involved in *ECB* and *RW* markets (scenario 4), in *ECB* and *HT*1 markets (scenario 5), and in *RW* and *HT*1 markets (scenario 6). In each case, the simulations assume that the merger leads to a monopoly in the corresponding market. The cases within scenario 4 allow the evaluation of possible efficiency gains that might emerge from mergers. Mergers across *ECB* and *RW* markets are associated with price reductions of \$5.99/bag for *ECB* seeds (scenario 4a), \$25.10/bag for *RW* seeds (scenario 4b), and \$31.09/bag for *ECB/RW* stacked seeds (scenario 4c). Merging *ECB* and *HT*1 is shown to have no impact on the *ECB* trait market (scenario 5a) but would induce a price increase of up to \$22.22/bag for *HT*1 seed (scenario 5b) and \$22.55/bag for *ECB*/*HT*1 stacked seeds (scenario 5c). Merging *RW* and *HT*1 could be associated with a price reduction of up to \$21.34/bag for *RW* seed (scenario 6a) and a price increase of up to \$19.91/bag for *HT*1 seed (scenario 6b). However, the price effects on *RW*/*HT*1 stacked seeds (scenario 6c) are not statistically significant.

Finally, the third set (scenarios 7–9) considers mergers involving biotech companies and traditional independent seed companies. Again, the simulations assume that the mergers lead to the monopolization in the

Table 5. Simulated Merger Effects

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* double	−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 double	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 double	−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

Note: Statistical significance is noted by an asterisk (*) at the 10% level, two asterisks (**) at the 5% level, and three asterisks (***) at the 1% level.

corresponding biotech trait market. However, since the monopolization of seed companies is unlikely (given many seed companies), the mergers in scenarios 7–9 are assumed to increase market concentrations for conventional seed only to the maximum observed in our sample. The results show that the merger involving *ECB* biotech firms leads to statistically significant price increases of up to $32.37/bag (scenario 7). The mergers involving *RW* biotech firms (scenario 8) and *HT*1 firms (scenario 9) do not generate statistically significant price changes. Importantly, these simulation results capture cross-market effects that play a significant role in the evaluation of the exercise of market power.

The simulations in table 5 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 spin-off effects by evaluating the 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 GHHI measures of market concentration. The model is applied to the U.S. corn seed market and is estimated using transaction-level data for the period 2000–2007. The U.S. corn seed industry is highly concentrated and involves conventionally bred hybrid seeds and other seeds with various combinations of patented GM traits that add value and service to the plant. 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 analyzed in this study, GM seeds were 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. The research findings yield several major conclusions. First, we find extensive evidence of spatial price discrimination. We observe that, *ceteris paribus*, 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 reflects the varying 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 GHHIs, this helps to document how traditional and cross-market effects of imperfect competition can contribute to higher (or lower) seed prices. For example, our results indicate that Lerner indexes are positive and statistically significant for three seed types. Fourth, our simulation of hypothetical mergers produced numerous interesting results. It documented how complementarity effects can contribute to lower prices. It also found that mergers between a biotech firm and a conventional seed firm can contribute to increasing the conventional seed price. Such a price increase may be of concern to policymakers if it contributes 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 investigate farmers' adoption behavior with a focus on dynamics and social learning in the presence of bundling and imperfect competition. Finally, there is a need to explore empirically the economics of bundling applied to other sectors. These appear to be good topics for further research.

Funding

Funded in part by the USDA NRI (grant no. 144-QS50) and USDA CSERRS Hatch grant (no. WIS01345).

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