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AN ANALYSIS OF BUNDLE PRICING:

THE CASE OF THE CORN SEED MARKET

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This paper investigates bundle pricing 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-Hirschmann 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 sub-additive bundle pricing. This result is consistent with the presence of scope economies in the production of genetic traits. The econometric estimates show how changes in market structures (as measured by both own- and cross-Herfindal indexes) affect U.S. corn seed prices.

Keywords: Bundling, component pricing, imperfect competition, seed, biotechnology

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1. Introduction

There has been much interest in the pricing of bundled goods by multiproduct firms. Three types of bundle pricing have been analyzed: component pricing where each component is priced separately and the effective price of products is the sum of their components; pure bundling where consumers are restricted to buy either a fixed bundle of components or nothing at all; and mixed bundling where products are offered both bundled and unbundled, each being priced separately. The industrial organization literature has examined how bundling and bundle pricing can help firms exercise market power under imperfect competition. This includes the price discrimination effects of bundling as a strategy to exploit heterogeneity of consumer preferences (e.g., Adams and Yellen 1976; Schmalensee 1984, McAfee et al. 1989; Venkatesh and Kamakura 2003; Fang and Norman 2006; Gans and King 2006). It also includes the use of bundling strategies as means of deterring entry or driving out rivals (e.g., Whinston 1990; Choi 1996; Carlton and Waldman 2002; Nalebuff 2004, 2005; Shi 2008a; Peitz 2008).

In general, which bundling strategy is better from the firm's viewpoint depends on the situation considered (Adams and Yellen 1976; McAfee et al. 1989; Venkatesh and Kamakura 2003; Fang and Norman 2006). Bundling can be motivated from the supply side in the presence of economies of scope (Adams and Yellen 1976). It can also be motivated from the demand side. When products are valued independently (i.e., when consumers' reservation value of a bundle is the sum of the reservation values of each component), McAfee et al. (1989) has shown that pure component pricing does not dominate if reservation values are independently distributed among consumers. And when purchases can be monitored, mixed bundling dominates (at least weakly) other bundling strategies (which can be seen as special cases of mixed bundling).

Going beyond the case where consumers' reservation values of components are independent, Venkatesh and Kamakura (2003) investigated the role of complementarity/ substitution in bundling decisions by a monopoly. By definition, components are complements (substitutes) when the reservation value of a bundle is super-additive (sub-additive) in the value of its components. They document how both degree of complementarity/substitution and production cost affect optimal bundling decision and pricing. They find that pure bundling dominates under strong complementarity regardless of cost levels. Pure component strategies are likely to dominate for substitutes, especially when production cost is high. And mixed bundling can dominate for weak substitutes or weak complements when production cost is low.

The implications of price discrimination for efficiency have been examined extensively in the literature (e.g. Schmalensee 1981; Holmes 1989; Corts 1998 and Armstrong and Vickers 2001). There are scenarios where bundling strategies can reduce the adverse effects of exercising market power (Adams and Yellen 1976; Brennan 2005; Shi 2008a). Also, if bundling strategies are motivated from the supply side in the presence of economies of scope, the production of multiple outputs by a single firm can reduce production cost and improve efficiency.

The empirical assessment of bundling and bundle pricing under imperfect competition raises significant challenges due to lack of data and a gap between theory and empirical validation of bundling.[1] We confront these challenges in three interdependent ways. First, we develop a model of bundle pricing under quantity setting games. In a multiproduct context, we show how the substitution/complementarity relationships among products with different sets of bundled characteristics can affect pricing. This is used to motivate multi-product generalizations of the Herfindahl-Hirschmann 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 competition and multiproduct pricing. The model also allows for a test of standard component pricing. Third, we present an empirical application to the US corn seed market. The econometric estimates provide useful information on interactions between bundling and market power.

The corn seed market presents a great case study for the analysis of bundling and bundle pricing under imperfect competition. Genetically modified (GM) corn acres account for about 80 percent of the total US corn acreage in 2007. GM corn seeds include patented genetic traits (such as insect resistance and/or herbicide tolerance) produced by biotech firms. These traits can be introduced into the seed either separately, or bundled together when multiple genetic traits are "stacked". In this context, bundled GM seeds refer to seeds with stacked genetic traits.

The last decade has seen a rapid rise in bundling in the US corn seed market. As documented below, the proportion of US 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 seeds were first commercialized in 1996. Two years later the double stacked corn seed (i.e. seed with two genetic traits) was introduced, followed by the introduction of the triple stacked system (i.e. the bundling of three traits), and then the quadruple stacked system in around 2006. Moreover, corn seeds with eight traits are expected to be released by Monsanto and Dow AgroScience by 2010 or sooner.

1 An evaluation of complex bundle pricing is presented by Chu et al. (2008). However, their analysis is based on numerical simulations.

The increased use of genetically modified and patented corn seeds has been associated with changing structure in the 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 seed 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 GM seed pricing and bundling.

Our econometric analysis quantifies the linkages between seed bundling, changes in market concentrations, and corn seed pricing. For bundled biotech traits, we reject standard component pricing of corn seed. We find strong evidence of sub-additive bundle pricing, which is consistent with price discrimination strategies and scope economies in the production of bundled seeds. We also find evidence of spatial price discrimination. The analysis captures the interactive role of market concentrations and complementarity/substitution in demand. We document how traditional and cross-market effects of imperfect competition affect 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) can affect seed prices.

The paper is organized as follows. Section 2 presents a conceptual framework of multiproduct pricing under imperfect competition. It develops a Cournot model introducing the GHHIs capturing cross-market effects of imperfect competition. Section 3 provides an overview of the US corn seed market. Section 4 presents our econometric model of seed pricing, where the GHHIs reflect the exercise of market power. The estimation method and econometric results are discussed in section 5. Sections 6 and 7 report the empirical findings and evaluate their implications. Finally, section 8 concludes.

2. THE MODEL

Consider a market involving a set $\mathbf{N} = \{1, ..., N\}$ of N firms producing a set $\mathbf{M} = \{1, ..., M\}$ of M outputs. Denote by $y^n \equiv (y_1^n, ..., y_m^n, ..., y_M^n) \in \Re_+^M$ the vector of outputs produced by the n-th firm, y_m^n being the m-th output produced by the n-th firm, $m \in \mathbf{M}$, $n \in \mathbf{N}$. 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: $\sum_{m\in\mathbf{M}} [p_m(\sum_{n\in\mathbf{N}} y^n) y_m^n] - C_n(y^n)$, 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

$$p_m + \sum\nolimits_{k\in\mathbf{M}} \tfrac{\partial p_k}{\partial y_m^n} y_k^n - \tfrac{\partial C_n}{\partial y_m^n} \leq 0, \tag{1a}$$

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

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

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 *M* products the firm chooses to sell.

Below, we consider the case of linear demands where $p_k = \alpha_k + \sum_{m\in\mathbf{M}} (\alpha_{km} \sum_{n\in\mathbf{N}} y_m^n)$, 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 $C_n(y^n)$ = $F_n(S^n) + \sum_{m\in\mathbf{M}} c_m y_m^n$, where $S^n = \{ j \in \mathbf{M} : y_j^n > 0\}$ is the set of positive outputs produced by the *n*-th firm. Here, $F_n(S^n) \geq 0$ denotes fixed cost that satisfies $F_n(\varnothing)$ = 0. And $\sum_{m\in\mathbf{M}} c_m y_m^n$ denotes variable cost, with constant marginal cost $\frac{\partial C_n(y^n)}{\partial y_m^n} = c_m$, $m \in \mathbf{M}$ for all $n \in \mathbf{N}$. Note that the presence of fixed cost (where $F_n(S^n)$ > 0 for $S^n \neq \varnothing$) 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 $F_n(\mathbf{M}_a) + F_n(\mathbf{M}_b) > F_n(\mathbf{M}_a \cup \mathbf{M}_b)$ for some $\mathbf{M}_a \subset \mathbf{M}$ and $\mathbf{M}_b \subset \mathbf{M}$, i.e. when the joint production of outputs y_a^n = $\{y_j^n : j \in \mathbf{M}_a\}$ and y_b^n = $\{y_j^n : j \in \mathbf{M}_b\}$ 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

$$p_m = c_m - \sum\nolimits_{k\in M} (\alpha_{km} \sum\nolimits_{n\in N} s_k^n s_m^n Y_k), \tag{2}$$

which can be alternatively written as

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

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 $m, k \in \mathbf{M}$.

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

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

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]

2 The markets shares are often expressed in percentage term in the calculation of the Herfindahl-Hirschman index. Then, the rule becomes Hmm > 1000 (Whinston 2008).

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 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 evolving market for US corn seeds.

3. The US Corn Seed Market

Our analysis relies on a large, extensive data set providing detailed information on the US corn seed market. The data were collected by **dmr**kynetec [hereafter DMR], St. Louis, MO. The DMR data come from a stratified sample of US corn farmers surveyed annually from 2000 to 2007.[4] The survey 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.[5]

3 Our model provide 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 The survey is stratified to over-sample producers with large acreage.

5 Thus, the DMR survey is not a true panel as the farm composition of the sample changes over time.

Since farmers typically buy their seeds locally, our analysis defines the "local market" at the Crop Reporting Districts (CRD)[6] level. On average each farm purchased four to five different seed varieties each year[7]. To guarantee reliable measurement of market concentrations, our analysis focus on those CRDs with more than ten farms sampled every year between 2000 and 2007. In total our data contain 149,919 observations from 91 CRDs in 18 different states.[8]

Starting in the 1930s, the development and diffusion of hybrid corn transformed the US seed industry and contributed to the dominant role played by private seed companies. With advances in breeding technology (including biotechnology) and institutional changes in the intellectual property protection of life forms since the 1980s, many small seed firms exited the market, and the seed industry is now dominated by few large companies (Fernandez-Cornejo 2004). The DMR data show that about 300 seed companies operate in the US corn seed market. However, only six biotech firms are involved,[9] four of which own subsidiary corn seed companies.[10]

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 focus on controlling damages caused by two insects: the European corn borer (*ECB*),[11] and rootworms (*RW*).[12] In corn biotech seeds, this means incorporating the *Bt* gene against the *ECB*, and the *Bt* gene against *RW*.[13] 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,

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

7 Due to the fast turnover in the seed market, farmers may try new varieties every year, thus would purchase more than one variety seed for their field. In addition, the US EPA requires that farmers maintain at least 20% of their cropland for non –"insect resistant" varieties.

8 They are: CA, CO, IL, IN, IA, KS, KY, MI, MN, MO, NE, NY, ND, OH, PA, SD, TX, and WI.

9 They are: Monsanto, Syngenta, Dow AgroSciences, DuPont, Bayer CropScience, and BASF.

10 While one of the two firms has already entered the cotton seed market, the DMR data show that it has not entered (yet) the US corn seed market.

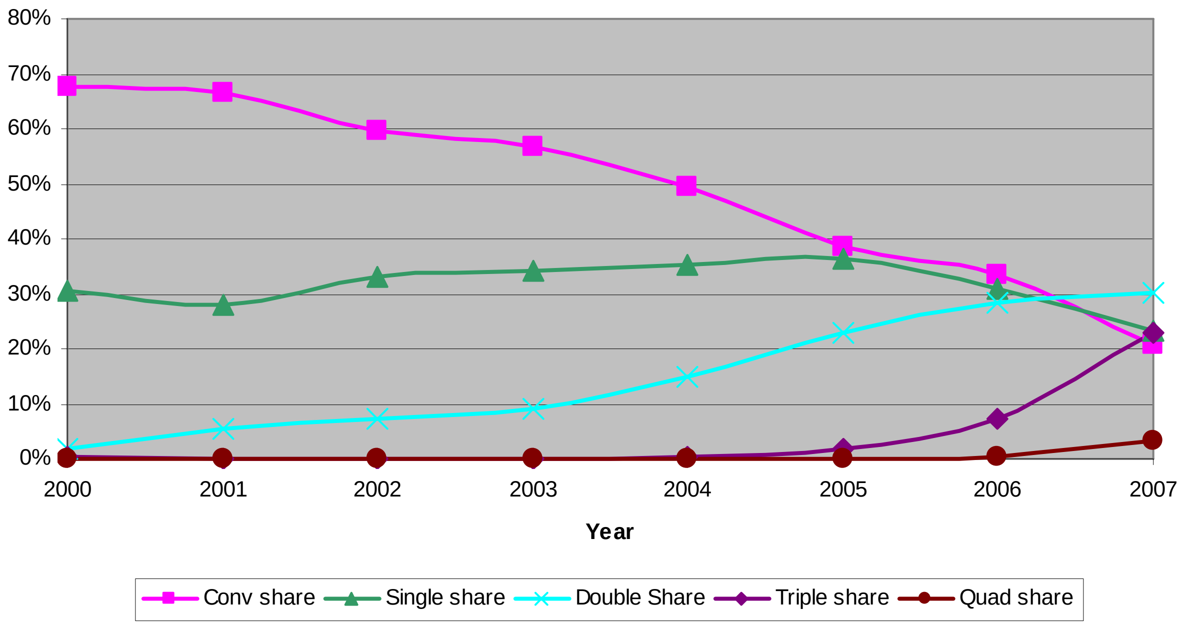
11 The European corn borer is a major pest of corn in North America and Europe. Yield loss due to ECB has been estimated to average about five percent, although damages can vary widely both over time and over space.

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

13 Bt is shorthand for a common soil bacterium called Bacillus thuringiensis. It also refers to the insecticide produced by a gene from these bacteria. In Bt corn, modified versions of this gene are introduced in corn plants where they kill selective insects.

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 corn seed ($ per bag) for different types 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.

Figure 1. Corn seed adoption rates in the US, acreage share, 2000 – 2007.



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 US market share of 30% in 2000, the DMR data show that conventional seeds still dominated many local markets. And while the US 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 US corn seed market. As shown below, such heterogeneity also applies to seed prices.

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

Year	Conventional	*Bt ECB Single*	*Bt 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

4. 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 section 2, 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 type, and let $\mathbf{Q} \equiv \{2, \ldots, J\}$ 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, $i \in \mathbf{Q}$, 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 $\sum_{i=1}^{J} K_i \geq 1$. Then, while K_i's provide information on the genetic characteristic of each seed, evaluating the effects of these 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 farm-variety 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). Consider the hedonic equation representing the determinants of the price *p* for a seed of characteristics $\{K_1, K_2, ..., K_J\}$:

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

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, with $K_{ij} = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix}$ if $\begin{Bmatrix} K_i = K_j = 1, K_z = 0 \text{ for } i \neq j \neq z \\ \text{otherwise} \end{Bmatrix}$, $i, j \in \mathbf{Q}$. Similarly, $K_{ijz} = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix}$ if $\begin{Bmatrix} K_i = K_j = K_z = 1, K_r = 0 \text{ for } i \neq j \neq z \neq r \\ \text{otherwise} \end{Bmatrix}$, and $K_{ijzr} = \begin{Bmatrix} 1 \\ 0 \end{Bmatrix}$ if $\begin{Bmatrix} K_i = K_j = K_z = K_r = 1 \text{ for } i \neq j \neq z \neq r \\ \text{otherwise} \end{Bmatrix}$ are dummy variables representing respectively triple-stacking and quadruple-stacking.[14]

In cases where the market is void of bundling/stacking of multiple traits, the dummy variables K_{ij}, K_{ijz} and K_{ijzr} equal zero. This implies that the coefficients δ_{ij}, δ_{ijz}, and δ_{ijzr} in (5a) capture the effects of bundling on seed price. The DMR data reveal that seed 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.

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14 Note that the K's in (5a) satisfy $\sum_{i\in\{1,...,J\}} K_i - \sum_{\substack{j\in\mathbf{Q}\\ j>i}} \sum_{i\in\mathbf{Q}} K_{ij} - 2\sum_{\substack{z\in\mathbf{Q}\\ z>j}} \sum_{\substack{j\in\mathbf{Q}\\ j>i}} \sum_{i\in\mathbf{Q}} K_{ijz} - 3\sum_{\substack{r\in\mathbf{Q}\\ r>z}} \sum_{\substack{z\in\mathbf{Q}\\ z>j}} \sum_{\substack{j\in\mathbf{Q}\\ j>i}} \sum_{i\in\mathbf{Q}} K_{ijzr} = 1$, implying that they are perfectly collinear with the intercept. To deal with this issue below, we set δ1 = 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.

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. 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

$$\delta_i = \delta_{0i} + \delta_{1i} H_{ii}, \tag{5b}$$

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 related to the *i*-th characteristic. We further specify

$$\beta = \beta_0 + \sum_{\substack{j \in Q \\ j > i}} \sum_{i \in Q} \beta_{1ij} HH_{ij}, \tag{5c}$$

where $HH_{ij} \equiv \begin{Bmatrix} H_{ij} \\ 0 \end{Bmatrix}$ if $K_i + K_j \begin{Bmatrix} > 0 \\ = 0 \end{Bmatrix}$, $i \neq j$, $H_{ij} \equiv \sum_{n \in N} s_i^n s_j^n$ being the cross-market GHHI discussed in section 2 and measuring concentration for firms operating in the market for both *i*-th and *j*-th seed type. With this specification, the coefficient of the traditional HHI, $\delta_{1i} > 0$, would reflect market power related to the *i*-th characteristic, while the coefficient of the GHHI, $\beta_{1ij} > 0$, would reflect the exercise of market power across characteristics.

Since 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

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

In a way similar to equation (4), equation (6) provides a structural representation of the role of imperfect competition in pricing. As noted in section 2, 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 effect of imperfect competition on price enhancement.

Our analysis is based on 5 seed characteristics (J = 5): Conventional $(K_1 = 1)$; insect resistance trait *Bt ECB* $(K_2 = 1)$; insect resistance trait *Bt 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 *HT1* and *HT2* are seen as different by farmers (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

$$p_1 = \beta_0 + \delta_{01} K_1 + \delta_{11} H_{11} K_1 + \sum_{j=2}^{5} \beta_{11j} HH_{1j} + \boldsymbol{\varphi}\mathbf{X} + \varepsilon. \tag{7a}$$

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

$$p_2 = \beta_0 + \delta_{02} K_2 + \delta_{22} H_{22} K_2 + \beta_{112} HH_{12} + \sum_{j=3}^{5} \beta_{12j} HH_{2j} + \boldsymbol{\varphi} \cdot \mathbf{X} + \varepsilon. \tag{7b}$$

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

$$\begin{aligned} p_{24} = \beta_0 + \delta_{02} K_2 + \delta_{04} K_4 + \delta_{24} K_{24} + \delta_{22} H_{22} K_2 + \delta_{44} H_{44} K_4 + \\ \beta_{112} HH_{12} + \beta_{114} HH_{14} + \sum_{j=3}^{5} \beta_{12j} HH_{2j} + \beta_{134} HH_{34} + \beta_{145} HH_{45} + \boldsymbol{\varphi}\mathbf{X} + \varepsilon \end{aligned} \tag{7c}$$

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. The first row of (7c) contains all the dummy variables reflecting stacking/bundling of traits along with their interaction effects with the traditional HHI's. The second row of equation (7c) contains the parameters linking price to the generalized cross market GHHI's. 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 section 7.

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. The location variables are defined as state dummy variables, capturing spatial heterogeneity in farming systems and agro-climatic conditions. 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%), followed by “Direct from seed company or their representatives” (29.4%), and “Myself, I am a dealer for that company” (15.7%). Note that farmers may choose different sources for different seed varieties. 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” in some local markets. Note that our model specification includes each H_{ii} only in interaction with K_i (with coefficient δ_{1i}). Similarly, the specification for HH_{ij} implies that the structural linkage between market concentration H_{ij} and pricing is present only when either K_i or K_j or both are non-zero, with $i \neq j$. In order to investigate whether entry/exit may affect seed prices beyond the *H*’s and *HH*’s 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 *HT1* trait (K_4) markets, the *Bt ECB* trait (K_2) markets and the *Bt RW* trait (K_3) markets. To capture entry-exit effects on seed price, the following binary terms are included in the model: $Exit1 = 1$ when $H_{11} = 0$; $Entry2 = 1$ when $H_{22} = 0$; $Entry3 = 1$ when $H_{33} = 0$; and $Entry4 = 1$ when $H_{44} = 0$.[15]

5. 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 exhibit greater competition than the biotech trait markets. For the 91 CRDs covering the eight years of our data, the average conventional seed HHI is 0.258. This is over 40% above the Department of Justice’s threshold of 0.18 for identifying "significant market power". 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 seems relevant as farmers typically buy their seeds locally and seed varieties vary with local agro-climatic conditions.[16] We observe significant changes in the *H*’s both across regions and over time. This reflects the fact that the corn seed market has undergone dramatic structural changes over the last decade. Our analysis of 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.

16 The average national HHI for the conventional corn seed markets from 2000-2007 is only 0.164, indicating that seed companies market in localized regions.

determinants of seed prices both over time and across space provides useful information on the effects of these changes.

Table 2. Summary statistics

Variable	Number of observations[a,b]	Mean	Standard Deviation	Minimum	Maximum
Price ($)	149910	97.94	26.49	0	230
Farm size (acre)	149919	593.31	634.90	5	15500
H_{11}	727	0.258	0.168	0.067	1
H_{22}	718	0.769	0.188	0.334	1
H_{33}	353	0.909	0.151	0.345	1
H_{44}	726	0.783	0.174	0.432	1
HH_{12}	673	0.040	0.037	2.09E-05	0.318
HH_{13}	321	0.037	0.030	1.40E-04	0.190
HH_{14}	653	0.033	0.034	5.54E-06	0.264
HH_{23}	351	0.760	0.174	0.166	1
HH_{24}	695	0.594	0.260	0.010	1
HH_{34}	351	0.794	0.201	0.085	1

[a]/ The data contain 149919 observations from 91 CRDs spanning 8 years (2000-2008). For the price, nine observations have missing value, thus the total number of observation becomes 149910.

[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 $91\times 8 = 728$.

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).[17] In our case, the *C* statistic is 92.94, showing strong statistical evidence against the null hypothesis of exogeneity of the *H*'s.

The presence of endogeneity motivates the use of an IV estimator. We used the lagged value of each *H* as instruments and conducted a series of tests supporting this choice. We estimated an Arellano-Bond dynamic panel regression of a reduced form model for the *H*'s that also includes lagged *H*'s as explanatory variables. The Arellano-Bond estimation allows for a test of serial correlation of the associated error term. Given lagged *H*'s, the test results failed to find evidence of serial correlation in the reduced-form error terms (reflecting unobservable factors affecting the *H*'s). This lack of serial correlation indicates that lagged *H*'s appear to be good candidates for instruments. On that basis, equation (5a)-(5c) was estimated by two-stage-least-square (2SLS), using one-period lag of the *H*'s for instruments. Further evaluation of these instruments is presented below.

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[18] found strong evidence against homoscedasticity of the error term in (5a). As reported in section 3, each farm purchases on average four to five different seed varieties. Some large farms actually purchase up to 30 different varieties 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 (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.[19] 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

17 Under conditional homoskedasticity, the C statistic is numerically equivalent to a Hausman test statistic.

18 Compared to the conventional 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).

19 Note that, since our model is just identified, the Hansen over-identification test is not applicable.

Kleibergen-Paap weak instrument test was conducted (Kleibergen and Paap, 2006),[20] yielding a test statistic of 14.67. Using the critical values presented in Stock and Yogo (2005), this indicated again that our analysis does not suffer from weak instruments.

6. EMPIRICAL RESULTS

Table 3 reports the IV regression results from our model using 2SLS method, with heteroscedastic-robust standard errors under clustering. We will 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 section 7, 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 (*Bt ECB*), K_3 (*Bt RW*) and K_5 (*HT2*) are each positive and statistically significant. They are respectively \$23.31, \$25.72, and \$7.38 per bag, suggesting the presence of significant premiums for these biotech traits. The coefficients of K_4 (*HT1*) and K_5 (*HT2*) differ, providing evidence of differences between the two herbicide-tolerant traits *HT1* and *HT2*. The coefficient of K_4 (*HT1*) is negative and statistically significant. However, note that the *K*'s also appear in interaction with the *H*'s and *HH'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 in section 7.

The coefficients of the terms K_{ij}, K_{ijz}, and K_{ijzr} provide useful information on the effects of bundling on seed price. All 11 of the stacking coefficients are negative, and all but K_{35} are statistically significant. As discussed in section 4, 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

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20 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).

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 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 HH_{ij} as given in equations (5a)-(5c). Here, we discuss the partial effects of concentration and withhold a global assessment of market concentration until section 7.[21] 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 effect on the price of conventional seeds. More specifically, a one-point increase in H_{11} is associated with a \$13.1 per bag increase in the price of conventional seeds. The partial effect of concentration in both insect resistant technologies, the *Bt-ECB* trait market (H_{22}) and the *Bt-RW* trait market (H_{33}), were statistically insignificant. Finally, the concentration effect in the *HT1* trait market is positive and statistically significant. A one-point increase in H_{44} is associated with a \$20.11 per bag increase in the price of *HT1* seeds.

We have shown in section 2 that the effects of cross-market concentration $HH_{ij},\ i \neq j,$ depend on the substitutability/complementarity relationship between traits *i* and *j*. We expect that an increase in the cross-market concentration HH_{ij} will be associated with a rise (decrease) in the price if the two components are substitutes (complements).

Of the three cross GHHI's that involves conventional seed $(HH_{12}, HH_{13}, HH_{14})$, only the coefficient on HH_{14} (conventional market share crossed with *HT1* market share) is of statistical importance. The positive effect of HH_{14} suggests that the *HT1* trait is a substitute with conventional seed. 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

21 We do not observe non-zero H_{15} because no firm that operates in HT2 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 characteristic market.

between this trait and conventional seed. The estimation shows that a one-point increase in H_{14} is associated with a $35.55 per bag increase in seed price.

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 *Bt-ECB* and *Bt-RW* cross-market effect (HH_{23}) is negative. This suggests that these two *IR* traits are complements. Since these two traits are targeting the control of different insects, this would reflect the fact that crop damages caused by one insect infestation are larger in the presence of damages from another insect infestation. The *Bt-ECB* and *HT1* effect (HH_{24}) and *Bt-RW* and *HT1* effect (HH_{34}) are positive, suggesting that these two *IR* traits and *HT1* trait are substitutes. This indicates that the effects of insect infestation on corn yield differ significantly from those for weed infestation.

Other Covariates

***Location effects*:** Compared to California, corn seed is sold at a premium in all states except Kentucky. The price premium is statistically significant in many states. Ordered from high to low premium, these states are: Nebraska ($7.50), Iowa ($7.00), Kansas ($6.86), Missouri ($6.31), Illinois ($5.96), Minnesota ($5.24), Colorado ($5.01), South Dakota ($4.75), Pennsylvania ($3.93), and Indiana ($3.70). This shows that the main corn-producing states in the Corn Belt charge more for corn seeds (e.g., Illinois or Iowa). This is consistent with corn belt farmers generating greater farm benefits from high-performing corn seeds under favorable agro-climatic conditions. It also suggests that seed companies do price discriminate across regions, reflecting spatial differences in elasticities of demand for seeds.

Purchase source effects: Recall that most farmers purchase seed from “Farmer who is a dealer or agent” (33%), followed by “Direct from seed company or their representatives” (29.4%), and “Myself, I am a dealer for that company” (15.7%). Compared to purchasing from “Farmer who is a dealer or agent”, “buying directly from a seed company or their representative” costs about $4.59 less, while purchasing from “myself” costs about $3.89 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.

Other variables: The exit and entry dummies are all negative but none are statistically significant. The entry dummies have relatively higher confidence levels, 81.2% for *Entry3,* 85.9% for *Entry2,* and 89.7% for *Entry4,* than that of the *Exit1* dummy (26.3%). Before the biotech seed’s entry, seed price tends to be lower. So the introduction of biotech seed may raise the price for all seeds, including the conventional varieties. This result is consistent with the finding in Shi (2008b), where she argues that the introduction of biotech seed can raise the conventional seed price.

Table 3. IV (2SLS) regression with robust standard errors,[a, b, c]

Dependant Var: Price ($/bag)	Coefficient	Robust z statistics
Characteristic effects, benchmark is K_1: Conventional seed		
K_2 (*Bt ECB*)	23.31***	7.82
K_3 (*Bt RW*)	25.72*	1.87
K_4 (*HT1*)	-6.68**	-2.32
K_5 (*HT2*)	7.38***	5.97
K_{23}	-16.43**	-7.66
K_{24}	-6.93***	-3.91
K_{25}	-3.70***	-2.82
K_{34}	-8.07***	-3.77
K_{35}	-1.49	-0.45
K_{45}	-16.97**	-2.25
K_{234}	-23.67***	-8.62
K_{235}	-19.94***	-4.97
K_{245}	-15.68***	-5.41
K_{345}	-12.02**	-2.48
K_{2344}	-28.87***	-6.61
Market concentration effects		
$H_{11}K_1$	13.13***	5.94
$H_{22}K_2$	-2.97	-1.02
$H_{33}K_3$	7.58	0.50
$H_{44}K_4$	20.11***	5.02
HH_{12}	17.22	1.52
HH_{13}	-58.19	-1.57
HH_{14}	35.55**	2.55
HH_{23}	-6.85***	-3.54
HH_{24}	6.68***	3.56
HH_{34}	6.82***	3.27
Other variables		
Exit1	-1.55	-0.34
Entry2	-2.90	-1.47
Entry3	-2.20	-1.32
Entry4	-5.37	-1.63
Total acre grown corn by each farm (1000 acre)	0.94***	5.45
Year	1.89***	13.81
Constant	71.82***	24.40
Number of observations	132813	

[a] Statistical significance is noted by * at the 10 percent level, ** at the 5 percent level, ** at the 1 percent level.
[b] The centered R^2 is 0.40, and un-centered R^2 is 0.96.
[c] Results for the location effects and purchase source effects are not reported here to save space, but are discussed in the text.

The farm size effect is statistically significant: large farms within each state pay more for corn seeds. This result is likely due to the fact that large farms are more productive than smaller farms and thus are willing to pay more for seeds. The farm size variable appears to capture another form of price discrimination used by seed companies in negotiating prices to individual clients. The time trend effect is positive and statistically significant. Seed price goes up on average by $1.89 per year. Given that the mean price is about $98, this gives a 1.93% increase a year, slightly less than the inflation rate over the same time period.[22] Therefore, in real terms, the seed price is decreasing over years, *ceteris paribus*,[23] reflecting technological improvements in the corn seed industry.

7. 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 a convenient choice: it is in the middle of our sample period; and it avoids entry/exit events for different 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

22 According to the Department of Labor statistics, the average inflation rate from 2000 to 2007 is 2.78%.

23 Our data suggest that the seed rate goes up slightly over years at a rate of about 0.7%. Even after this factor into consideration, seed prices are still increasing at a lower rate than inflation.

relevant variables for Illinois in 2004 (including farm size, the traditional HHIs (H_{ii}) and the cross market GHHIs (HH_{ij})).[24]

Table 4 contains the simulation results.[25] The simulated mean conventional seed price is $89.78/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% 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 standalone biotech trait. Adding the *Bt-ECB* trait (K_2) alone raises the seed price by a premium of $19.04. The corresponding price premium is $25.84 for *Bt-RW* (K_3), $13.06 for *HT1* (K_4), and $5.38 for *HT2* (K_5).

Double, triple, and quadruple-stacked seed prices and premiums are presented in cases 6-15. Note first the $34.07 premium for stacking *Bt-ECB* and *Bt-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 (19.04 + 25.84 = $44.88). A similar pattern is evident in all the double stacked seed prices. The triple stacking of *Bt-ECB*, *Bt-RW* and *HT1* traits (K_{234}) has a price premium of $35.85. While this is greater than the value of any individual trait component or any relevant double stacked seed price, it is less than the sum of the individual premiums ($57.94). 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 single traited system (to form a double stacking system) or alone (to form a single traited system). Other triple stacking systems follow the same pattern. Finally, the price premium for quadruple stacking (K_{2345}) is $39.45, which is the highest among all scenarios. As before, the marginal contribution of each individual trait is again lower than in a triple system.

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

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

25 Note that we did not simulate the case for HT1 trait stacked with HT2 trait (K_{45}) because we have very few observations on the K_{45} stacking system. The same applies for K_{245}.

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.

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

Case	Traits	Expected Seed Price	Price difference from K_1 (Conventional)
1	K_1 (Conventional)	89.78 (0.79)	0.00
2	K_2 (*Bt-ECB*)	108.82 (0.79)	19.04*** (0.39)
3	K_3 (*Bt-RW*)	115.62 (5.22)	25.84*** (5.22)
4	K_4 (*HT1*)	102.84 (0.86)	13.06*** (0.40)
5	K_5 (*HT2*)	95.16 (0.91)	5.38*** (0.58)
6	K_{23}	123.84 (3.71)	34.07*** (3.67)
7	K_{24}	113.84 (1.19)	24.06*** (0.73)
8	K_{25}	112.51 (0.95)	22.73*** (0.67)
9	K_{34}	119.69 (3.93)	29.91*** (3.95)
10	K_{35}	121.48 (3.28)	31.70*** (3.22)
11	K_{45}	93.27 (7.54)	3.50 (7.48)
12	K_{234}	125.63 (3.21)	35.85*** (3.21)
13	K_{235}	127.69 (2.42)	37.91*** (2.34)
14	K_{245}	112.48 (1.48)	22.70*** (1.14)
15	K_{345}	123.07 (1.48)	33.29*** (4.47)
16	K_{2345}	127.78 (2.22)	38.03*** (2.21)

[a] Standard errors are in parentheses. Statistical significance is noted by * at the 10 percent level, ** at the 5 percent level, and *** at the 1 percent level.

Estimated Lerner indexes

As discussed in sections 2 and 4, 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 $L = \frac{M}{p}$. Using equation (6), this provides a convenient way of evaluating the Lerner index *L*. 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 five cases (out of eight cases).[26] When significant, the Lerner indexes are always positive, with estimates of ($100 \times L$) varying from 2.25% for conventional seeds (K_1) to 21.14% for *HT1* (K_4). 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. Also, this effect is found to be significant and fairly large in the bundled-seed markets involving *HT1*, with ($100 \times L$) equal to 14.39 for K_{24} (*Bt-ECB* and *HT1*), 17.62 for K_{34} (*Bt-RW* and *HT1*), and 15.32 for K_{234} (*Bt-ECB*, *Bt-RW* and *HT1*). Finally, the Lerner indexes are not statistically different from zero for K_2 (*Bt-ECB*) and K_3 (*Bt-RW*). Thus, our analysis does not find empirical evidence that market power has a significant effect on seed prices in these two sub-markets.

Table 5 Simulated Lerner Indexes[a]

	Lerner Index ($100 \times L$)	Standard Error	t-ratio
K_1 (Conventional)	2.25*	1.236	1.818
K_2 (*Bt-ECB*)	-2.06	2.840	-0.724
K_3 (*Bt-RW*)	2.05	7.573	0.271
K_4 (*HT1*)	21.14***	2.539	8.325
K_{23}	2.88	5.755	0.500
K_{24}	14.39***	3.273	4.396
K_{34}	17.62**	7.614	2.314
K_{234}	15.32**	6.113	2.506

[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.

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

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. It means that 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. 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*). Note that these merger scenarios are counterfactual: such mergers have not been observed. They are presented to illustrate how our analysis can be used to evaluate the price implications of changing market structures. Again, our simulation analysis focuses on the state of Illinois in 2004. The results are reported in Table 6.

Table 6 presents the price effects of selected merger scenarios. Scenarios 1-3 consider mergers between biotech companies within a given genetic trait market (*biotech/biotech within trait*). This covers mergers of biotech firms within the *Bt-ECB* market (scenario 1), within the *Bt-RW* market (scenario 2), and within the *HT1* market (scenario 3). In each case, the simulations assume that the merger leads to a monopoly in the corresponding market (with a market share equal to 1).[27] In scenarios 1-3, Table 6 shows that the effect of such mergers on seed price would not be statistically significant for *Bt-ECB* and *Bt-RW*. However, the effect is statistically significant for *HT1*. Our simulation results show that mergers of biotech firms in the *HT1* markets could potentially induce a price increase of up to \$23.44/bag of *HT1* seed.

Scenarios 4-6 consider mergers between biotech companies producing different genetic traits (*biotech/biotech across traits*). This covers mergers of biotech firms involved in *Bt-ECB* and *Bt-RW* markets (scenario 4), in *Bt-ECB* and *HT1* markets (scenario 5), in *Bt-RW* and *HT1* 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 effect of mergers across *Bt-ECB* and *Bt-RW* markets would have no statistically significant effect on the price of either *Bt-ECB* seeds (scenario 4a) or *Bt-RW* seeds (scenario 4b) or *Bt-ECB/Bt-RW* stacking seeds (scenario 4c) at 5% level. However, the price effects of mergers "across traits"

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27 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.

involving *HT1* are found to be statistically significant. In particular, mergers involving *Bt-ECB* and *HT1* could potentially induce a price increase of up to $12.23/bag of *Bt-ECB* seed (scenario 5a), $24.88/bag of *HT1* seed (scenario 5b), and $30.43/bag of *Bt-ECB*/*HT1* stacking seeds (scenario 5c). And mergers involving *Bt-RW* and *HT1* could generate a price increase of up to $25.02/bag of *HT1* seed (scenario 6b). However, the price effects on *Bt-RW* seeds (scenario 6a) and on *Bt-RW*/*HT1* stacking seeds (scenario 6c) are not statistically significant.

Finally, scenarios 7-9 consider mergers involving both biotech companies and seed companies (*biotech/seed merger*). In these scenarios, 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*'s and *HH's*) only to the maximum observed in our sample. How do mergers involving both seed companies and biotech firms affect seed prices? The simulation results reported in Table 6 shows that such mergers can have a statistically significant impact on the price of conventional seed. The simulated effect is up to +$17.94/bag when mergers involve *Bt-ECB* biotech firms (scenario 7) and +$31.21/bag when the mergers involve *HT1* firms (scenario 9). However, our simulations indicate that the effects of such mergers would not be statistically significant when it involves *Bt-RW* biotech firms. 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.

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 and proceeding with a quantitative assessment of the price effects. Alternatively, the model could be used to estimate the effects of spinoffs by evaluating their anticipated effects on HHIs and GHHIs and by simulating the associated price changes.

Table 6: Simulated Merger Effects[a]

Sector affected by mergers	Scenarios	Market/Price Affected	Induced price change ($/bag)	Standard Error	t-ratio
Bt-ECB (K_2)	1	*Bt-ECB* (K_2)	6.61	4.14	1.595
Bt-RW (K_3)	2	*Bt-RW* (K_3)	-17.57	14.67	-1.197
HT1 (K_4)	3	*HT1* (K_4)	23.44***	5.36	4.374
Bt-ECB and *Bt-RW* (K_2, K_3)	4a	*Bt-ECB* (K_2)	-1.30	4.32	-0.300
	4b	*Bt-RW* (K_3)	-24.73*	14.89	-1.661
	4c	*Bt-ECB/Bt-RW* (K_{23})	-19.19	14.62	-1.312
Bt-ECB and *HT1* (K_2, K_4)	5a	*Bt-ECB* (K_2)	12.23***	4.62	2.649
	5b	*HT1* (K_4)	24.88***	5.97	4.169
	5c	*Bt-ECB*/*HT1*(K_{24})	30.43***	6.30	4.832
Bt-RW and *HT1* (K_3, K_4)	6a	*Bt-RW* (K_3)	-11.07	15.06	-0.735
	6b	*HT1* (K_4)	25.02***	5.08	4.923
	6c	*Bt-RW/HT1* (K_{34})	7.13	14.02	0.508
Conv. and *Bt-ECB* (K_1, K_2)	7	Conventional (K_1)	17.94**	8.42	2.131
Conv. and *Bt-RW* (K_1, K_3)	8	Conventional (K_1)	-37.59	27.61	-1.362
Conv. and *HT1* (K_1, K_4)	9	Conventional (K_1)	31.21***	10.1	3.091

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

8. CONCLUDING REMARKS

This paper has presented an analysis of bundle pricing under imperfect competition. A multiproduct model under Cournot competition 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 US corn seed market and estimated using farm-level data from 2000-2007. The US corn seed market represents a unique opportunity to evaluate the pricing of bundled goods, where patented genetic traits are inserted into conventionally bred hybrid corn seeds 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 US 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 imperfect competition. It finds evidence of spatial price discrimination. It captures the interactive role of market concentrations and complementarity/substitution. We find strong evidence of sub-additive bundle pricing, thus rejecting standard component pricing. This is consistent with the presence of economies of scope in seed production. Using generalized HHI's, we also document how traditional and cross-market effects of imperfect competition can contribute to higher seed prices. The analysis is used to illustrate how changing market concentrations can affect seed prices.

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 topics for further research.

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