Innovation, Licensing, and Competition: Evidence from Genetically Engineered Crops

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Abstract

We provide a novel empirical analysis of the role of technology licensing, between competitors, for genetically engineered (GE) traits in the US seed industry. We extend the standard differentiated-product Bertrand pricing model to include trait licensing, which permits us to recover marginal costs and (otherwise unobserved) royalty rates. Estimation relies on a large dataset of farm-level seed purchases. We find that markups over marginal cost are sizeable, and royalties for GE traits contribute a non-trivial amount to these markups. Notwithstanding its strategic effect on pricing, licensing of GE traits to competitors actually has net positive impacts for all market participants.

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1. Introduction

Increasing consolidation in many industries has rekindled concerns about market power and its possible broad impacts on the US economy (Shapiro 2018; Berry, Gaynor, and Scott Morton 2019; Syverson 2019; De Loecker, Eeckhout, and Unger 2020). In syntony with this debate, the Biden administration issued a far-reaching executive order on promoting competition in the American economy (White House 2021), which singled out the seed industry as deserving special attention. A major source of apprehension is that intellectual property, while incentivizing innovation, may have detrimental effects on competition (USDA-AMS 2023). To a large extent, competitiveness issues in the seed industry can be traced to both the emergence of biotechnology as a key source of innovation and the parallel strengthening of intellectual property rights for biological innovations, which led to the development of genetically engineered (GE) crop varieties (Clancy and Moschini 2017).

Unlike other waves of technical progress that transformed agriculture in the twentieth century, largely credited to publicly sponsored research (Gollin, Hansen, and Wingender 2021), the development of GE crop varieties was spearheaded by private research and development (R&D) activities by US seed companies, with Monsanto playing a leading role. In fact, Monsanto did not have a seed business when it developed (and patented) the original GE traits, but it promptly embarked on a series of acquisitions that, over time, transformed it into the largest seed company in the world. Monsanto also pursued a parallel strategy of aggressively licensing GE traits to other seed companies. Indeed, a distinctive feature of the seed industry is that diffusion of GE traits has relied considerably on licensing. Although Monsanto remains the most successful GE innovator, other seed companies have also developed and licensed GE traits. The industry is thus characterized by a web of cross-licensing arrangements, which offers a unique opportunity to investigate the competitive and welfare implications of technology licensing.

Whereas our pursuit is squarely empirical, the analysis in this paper builds on the extensive theory of licensing proprietary innovations that originated with Arrow (1962). Prior work specifically centered on patent licensing has focused on the form of licensing contracts (e.g., a flat-fee per license, possibly determined by an auction mechanism, or per-unit royalties) and the role of licensing for R&D incentives. Most studies consider the case when the innovator is an outside entity not engaged in production (e.g., an R&D lab), in which case licensing by a fixed fee is typically preferable (Kamien and Tauman 1986; Katz and Shapiro 1986). A different scenario arises when the innovator is also engaged in production, which is the case in our study, such that licensing involves the transfer of a new technology to competitors. Still, Katz and Shapiro (1985) show that there is always a license agreement that dominates no licensing for both the licensor and licensee. In particular, in this situation, the innovating firm typically prefers to license its technology via per-unit royalties (Wang 1998; Kamien and Tauman 2002).

Cross-licensing has long been recognized as an effective solution (along with patent pools) for the problem of fragmented and overlapping patent rights (Shapiro 2000). But, it has long been recognized that cross-licensing also raises competitiveness concerns (Priest 1977). By essentially taxing each other, firms can use cross-licensing arrangements to implement collusive outcomes (Shapiro 1985). Fershtman and Kamien (1992) provide an illustration for a duopoly with per-unit royalties. Jeon and Lefouili (2018) extend this basic result to an industry setting with many firms. Importantly, their generalization applies not only under multilateral bargaining involving all firms, but also when the mechanism is that of privately-negotiated bilateral cross-licensing agreements.[1]

Whereas much of the literature has focused on the licensing of a cost-reducing innovation in Cournot oligopoly, GE traits involve the licensing of product innovations in a differentiated-product industry. In fact, from the point of view of traditional seed producers, GE traits are essential inputs. A firm such as Monsanto, which has vertically integrated the production of GE traits with traditional breeding activities, clearly has the strategic opportunity to raise rivals' costs by its pricing of the essential inputs (GE traits) it controls (Salop and Scheffman 1983). More generally, because GE traits improve the quality of seed products, the innovation being licensed affects users' preferences and thus has a direct effect on the demand facing licensees and licensor

[1] Notwithstanding the potential for collusion in this setting, however, the monopoly outcome with cross-licensing may be superior, from a welfare perspective, to a competitive outcome without the exchange of a (complementary) technology.

when (as in the case of GE traits) the innovator is also engaged in production. The strategic implications of licensing in this setting can be subtle. A strand of literature pertinent to this context focuses on the licensing of premium content in the pay-TV market (Harbord and Ottaviani 2001; Stennek 2014; Weeds 2016). Conclusions germane to our setting include that, in a differentiated-product industry, the owner of a premium product may in fact want to license it to its competitors—provided it can do so on a per-unit fee. This arrangement not only raises competitors' costs, it also increases the licensor's opportunity cost. Such licensing agreements, therefore, can be an effective mechanism to relax downstream price competition and more fully extract consumer surplus.

In this paper we provide an empirical investigation of licensing in the US seed market. Despite a relatively rich theoretical literature on the licensing of proprietary innovations, empirical applications are exceedingly rare.[2] The (typically) undisclosed nature of information regarding licensing agreements can perhaps explain this gap in the literature. Furthermore, as noted by Shapiro (1985, p. 26) in his lucid discussion of patent licensing, "*… licensing among rivals is not often observed in practice*." The corn and soybean seed industry that we study in this paper, by contrast, clearly exhibits widespread licensing of GE traits. Building on the theoretical literature discussed above, we develop a model that explicitly represents GE trait licensing in a way that captures the salient attributes of the seed industry—multiple seed companies that sell (horizontally) differentiated products, compete in prices, and engage in extensive licensing of GE traits (both as licensors and licensees). The backbone of the empirical analysis is a seed demand model that we estimate based on a unique dataset assembled by Kynetec Inc., USA. These data comprise a representative sample of farm-level seed purchases by US soybean and corn farmers over the period 1996–2016. We also rely on publicly available data sources to assign ownership of GE traits, including the biotech/GE crop approval database maintained by the International Service for the Acquisition of Agri-biotech Applications (ISAAA).

[2] One exception is Hausman and Leonard (2007), who consider the hypothetical minimum acceptable (flat-fee) royalty for a patent holder in a market with four (unidentified) goods.

This paper makes some key novel contributions. In particular, we extend the standard Bertrand differentiated-product model to include per-unit royalties between licensors and licensees. Using the estimated demand parameters, we establish identification conditions which allow us to recover *both* marginal costs and the (unobserved) royalty rates—to the best of our knowledge, this is the first study to do so. Our framework rests on two key assumptions: licensing takes the form of per-unit royalties; and, royalty rates are taken as given when firms make their pricing decisions. The first of these conditions may appear restrictive, but is arguably suited to the empirical context we consider. As noted earlier, when both the licensor and licensee are engaged in production, the innovating firm typically prefers to license its technology via per-unit royalties—this licensing contract gives the licensor a cost advantage in the subsequent price competition stage. Second, the assumption that royalty rates are taken as given prior to firms' pricing decisions reflects the nature of licensing in the seed industry. The transfer of GM traits requires the insertion of biological material into the seed germplasm owned the licensee (e.g., by backcrossing), which requires considerable time (Ciliberto, Moschini, and Perry 2019). Thus, although the licensing terms are undisclosed, it seems reasonable to postulate that long-term arrangements are needed to account for these fundamental technological constraints.

The estimated model permits an in-depth assessment of the welfare effects of GE trait innovation and the role of licensing in this context. Corn and soybean seed prices have increased dramatically over the last two decades. This pattern is, of course, consistent with the fact that farmers attach value to the GE traits embedded in modern corn and soybean seed varieties (Ciliberto, Moschini, and Perry 2019). Licensing and cross-licensing contracts for GE traits, however, also affect the ability of the seed industry to exercise market power. We show that the existence of royalties significantly adds to the standard markup of a differentiated-product Nash equilibrium, and specifically that licensing to competitors has a strategic effect on prices (for products not paying any royalties, for example, this strategic effect increases the standard price markup by about one-third).

We use the estimated model to perform counterfactual experiments to analyze policy-relevant scenarios. The benchmark case of no royalties—whereby public research implicitly provides the observed GE traits for free—shows a sizeable welfare gain of $469 million per year (constant 2011 dollars). Separately, the hypothetical case of full collusion by seed providers shows a very large welfare loss, with farmers' surplus declining by $9,533 million per year, with about two-thirds of this amount captured by seed firms as extra profit. These results are rooted in the very inelastic nature of seed demand, ultimately due to the essential fixed proportion between seed and land used by farmers. With such an inelastic demand, the seed industry behaving as a monopolist would choose to increase prices steeply, relative to the baseline—124% for maize and 183% for soybean seeds. The potential for such large price impacts justifies the antitrust-related policy attention that the seed industry has garnered over the last few decades. Finally, we ask whether GE licensing is desirable, relative to exclusive use of GE traits by their owners. The case of soybean glyphosate tolerance (GT) provides an ideal setting to investigate this question. We find that Monsanto's decision to license the GT trait improved its profits, as well as those of licensees, and also resulted in higher farmers' surplus. The total surplus of the seed industry and farmers combined increased by an estimated $750 million per year because of soybean GT licensing, relative to exclusive use of the GT trait by Monsanto. This result provides unique empirical evidence on the welfare-enhancing role of technology licensing.

The rest of the paper is organized as follows. Section 2 offers a brief background on the development of GE crops, and how licensing of GE traits emerged as a major feature of the seed industry. Section 3 provides some descriptive statistics on market shares and product prices in the corn and soybean seed industry. Section 4 shows how to embed royalty rates for licensing and cross-licensing of GE traits in a Bertrand-Nash model of differentiated products. Section 5 lays out the two-level nested-logit demand model that provides the backbone for the empirical analysis. Section 6 reports the demand estimation results as well as the estimated royalty rates for GE traits. Section 7 considers several counterfactual experiments that elucidate the competitive implication of licensing, and the exercise of market power, in the seed industry. Section 8 concludes.

2. Genetic Engineering and the Seed Industry: The Early Years

The "GE revolution" is most clearly exemplified by the two most important crops in US agriculture, corn and soybeans—within ten years of their introduction in 1996, GE varieties accounted for more than 60% of planted corn acres and more than 90% of planted soybean acres (Moschini 2008). Unlike the earlier "green revolution," which was the result of substantial research efforts by public institutions (Gollin, Hansen, and Wingender 2021), the private sector led the way in the "GE revolution," with Monsanto playing a key role. Monsanto's journey to commercializing its GE innovations is critical to understand the industry shake-up caused by GE products, and the emergence of GE trait licensing.

In the early 1980s Monsanto was a company focused on agricultural chemicals. Its best-selling product was Roundup, a broad-spectrum herbicide (with glyphosate as the active ingredient) that killed most living plants. Monsanto discovered that some bacteria, however, had evolved the ability to survive exposure to glyphosate, and its scientists succeeded in splicing the relevant gene of resistant bacteria into plants. From the beginning, it was clear that, for GE traits to be successful, seed companies needed to embed them in seed varieties farmers would want to buy. The technology of splicing a bacteria gene into a plant, using recombinant DNA techniques, was developed in the late 1980s, with contributions from several sources. Monsanto partnered with Agracetus (a biotech startup that had mastered the "biolistic gun" transformation method) and with Asgrow (a seed company) to develop GE seeds that they could eventually commercialize. Still, spurred on by their company's impatient corporate pressure, Monsanto sought an arrangement with the largest seed company at the time, Pioneer. The 1992 deal was remarkable—for the modest one-time payment of half a million dollars, Pioneer obtained the right to use Monsanto's "Roundup Ready" (RR) technology in its soybean varieties in perpetuity. As Charles (2002) put it, "*Pioneer walked away with Monsanto's crown jewel basically for free…*".

From an economics perspective, GE traits and germplasm are truly "complementary" assets (Graff, Rausser, and Small 2003). Optimal exploitation of their potential value requires vertical integration or effective licensing. As Yogi Berra famously put it, "*When you come to a fork in the road, take it*," and this is what Monsanto did. It sought to vertically integrate with seed companies who possessed the suitable commercial wherewithal, acquiring Dekalb (strong in corn) in 1997, Asgrow (strong in soybeans) in 1998, and Holden (having a broad collection of corn foundation seeds) in 1998. Concomitantly, Monsanto pursued a strategy to license its GE traits to other seed firms. Getting seed firms to accept onerous license terms was half the battle. An equally serious one was to convince farmers to pay for the new technology. This was particularly important for soybeans, an open-pollinated crop that reproduces true-to-type.[3]

The RR trait was patented, though, unlike the underlying germplasm (at the time), which provided an avenue to use standard contract law to avoid the "seed saving" trap. Seed companies that agreed to license the Monsanto GE trait would charge a "technology fee" to farmers to reflect the cost of their licenses; and, they would require farmers to sign a "technology agreement" preventing them, among other things, to resell seed, and to use the seed for planting a single commercial crop (i.e., no "seed saving" allowed). The technology fee collected at the point of sale was an instrument for Monsanto to collect per-unit royalties, but it is important to understand the multiplicity of objectives that Monsanto was pursuing at the time. Monsanto shared some of the fee with seed companies to enlist their help in the effort to build up farmers' demand for GE varieties, and to ensure compliance by farmers with the novel restrictive sales contract clauses.

Another point that bears on Monsanto licensing and pricing incentives concerns one of the initial motivations to develop RR crops—a way to promote increased sales of the herbicide Roundup. This was a very lucrative product, and Monsanto, still holding a valid US patent in the 1990s, had a monopoly on the glyphosate market. Hence, charging royalties on RR seeds was not the only way for Monsanto to monetize the commercialization of this technology. Monsanto's glyphosate patent would eventually expire in 2000 and, within a few years, entry of generic competitors would erode Monsanto's profitable position in the glyphosate market (Perry, Hennessy, and

[3] This means that farmers can effectively use harvested seeds for next year's plantings. Indeed, "seed saving," a practice permitted by the then-prevailing intellectual property rights for plants, was an important practice in the early 1990s (and, beyond its actual use, it provided an "outside option" for farmers which drastically limited commercial soybean seed price premia).

Moschini 2019). From then onward, GE royalties or direct seed sales took on an increased relevance as value-capture instruments for the company.

In the 1990s, as Monsanto pursued its seed company acquisitions—with the likely dual objective of having a direct commercialization channel for its GE traits, and to strengthen its bargaining position vis-à-vis licensees of its GE traits—the seed industry itself was going through major upheavals. The driving force was the idea of "life science companies"—the bringing together pharmaceutical, agro-chemical, and seed businesses with the belief that this would create major synergistic opportunities. The concept was short-lived (Morrow 2000), however. As the wave of mergers and de-mergers settled by the year 2000, the fundamental structure of the corn and soybean seed industry had been established, although other, smaller acquisitions would be made in subsequent years.[4] The re-structuring of the seed industry also offered Monsanto the opportunity to address an earlier mis-step. Monsanto sued DuPont, and courts ruled that, indeed, the 1992 soybean deal became void when DuPont acquired Pioneer in 1999. This and other related lawsuits between the parties eventually settled out of court in early 2002. The terms were undisclosed, but it was reported that Pioneer would henceforth pay royalties to Monsanto, but would apparently not pay for past damages (Pollack 2002).

As Monsanto looked to exploit its GE trait licensing operations at the end of 2001, it discontinued the "technology fee" practice. Rather than farmers seeing a separate item on their seed invoice, Monsanto shifted to a royalty pricing system whereby the seed companies who licensed GE traits paid royalties directly, but they were free to price the fee into their seed products. The fee mechanism had achieved its (multiple) goals. As noted by a Monsanto executive at the time, "*The technology fees have worked well to show growers the cost of technology …*," hastening to add: "*We don't want growers to get the wrong perception … we are not saying we're lowering the cost of the system to the seed company.*" (Anon 2001).

The year 2002 thus emerges as a natural watershed. Monsanto had successfully established a strong bargaining position, by securing a steady foothold in the seed industry and by

[4] See Fernandez-Cornejo (2004), Heisey and Fuglie (2011), and Ciliberto, Moschini, and Perry (2019) for additional details and discussion. MacDonald (2019) covers more recent developments.

strengthening its intellectual property claims. Early licensing missteps with their biggest seed competitor, Pioneer/DuPont, resolved through lawsuits. The spectacular success of GE varieties with farmers—which went beyond reasonable expectations prior to their commercialization—guaranteed a strong demand for GE products and, indirectly, for Monsanto's GE traits. Newer GE traits were at the brink of commercialization (e.g., the *Bt* rootworm trait), and the "stacking" of multiple GE traits into the same variety was just beginning. Monsanto had jettisoned the "technology fee" pricing strategy in favor of a royalty system, and could now look forward as the dominant player in what promised to be a lucrative GE licensing business.

3. The US Corn and Soybean Seed Market

The primary data employed in this study are comprised of farm level observations for US corn and soybean farmers, from 1996–2016, collected by Kynetec USA, Inc., a market research company that specializes in agriculture data. The data are based on annual surveys of approximately 4,732 randomly sampled US corn farmers and 3,560 randomly sampled soybean farmers per year, with the samples designed to be representative at the CRD level. [5] The survey responses contain information on the seed type (brand and embedded GE traits), quantities, and cost. To construct the GE trait licensing relationship between seed firms, we supplement these data with the biotech/GE crop approval database, which is publicly available and maintained by ISAAA. For the actual estimation of the demand model, we restrict the sample to the top 13 corn and soybean producing US states. See Appendix A for more details.

3.1 Seed Market Shares

The wave of mergers and acquisitions that took place during the 1990s had largely settled by 2002, with AgReliant, Dow AgroSciences, DuPont, Monsanto, and Syngenta emerging as the largest firms in the industry. **Table 1** provides three-year average market shares over three separate time intervals during the 2002–2016 period.

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[5] CRDs (crop reporting districts) are regions defined by National Agricultural Statistics service of the US Department of Agriculture. A CRD, larger than a county and smaller than a state, encompasses a region with similar growing conditions.

In the corn seed market, the most significant development was the rapid expansion of Monsanto's market share of more than twenty percentage points from the 2002–2004 period to the 2008–2010 period. This came primarily at the cost of local and regional companies, which saw a corresponding decline in market share. Monsanto's expansion was in part due to their leading position in GE products, but they also continued to add smaller brands to their portfolio throughout the 2000s. Other companies such as AgReliant and Syngenta also expanded, whereas the previous dominant firm, DuPont (owner of Pioneer), experienced a slight decline in market share. In the soybean market, similar changes took place, albeit to a lesser extent. Monsanto increased their share from 21.9% (2002–2004) to 31.1% (20014–2016). Syngenta and even DuPont saw moderate increases in market share as well, all primarily to the detriment of local and regional companies. By the final period in our analysis, DuPont and Monsanto were the clear market leaders, with Syngenta, Dow, and AgReliant holding a smaller, albeit significant, share in the market.

Table 1. Market Shares in the US Corn and Soybean Seed Industry, 2002–2016

	2002–2004	2008–2010	2014–2016
CORN			
AgReliant	3.8%	6.1%	6.6%
Dow AgroSciences	4.6%	4.0%	4.9%
DuPont	34.9%	31.0%	32.8%
Local and regional companies	38.6%	17.5%	16.0%
Monsanto	12.4%	33.7%	34.1%
Syngenta	5.7%	7.6%	5.6%
SOYBEANS			
AgReliant	1.6%	1.8%	2.2%
Dow AgroSciences	2.9%	2.5%	4.3%
DuPont	23.3%	27.5%	28.9%
Local and regional companies	43.3%	27.2%	25.1%
Monsanto	21.9%	29.0%	31.1%
Public/Saved seed	2.0%	1.1%	0.7%
Syngenta	5.1%	10.8%	7.7%

Note: This table reports the market shares, computed as % of planted acres, for selected three-year periods. Source: Authors' calculation on Kynetec data.

3.2 GE Technology Adoption

The success of GE traits is exemplified by how rapidly they were adopted. **Table 2** provides GE adoptions rates for select years during the 1996–2016 period. Within just eight years from their inception (1996), GT soybeans had reached nearly 90% adoption. Farmers adopted GE corn varieties at a slower rate, but still achieved nearly 90% by 2010. Initially, only single trait varieties were available in limited quantities. Hybrids engineered to be resistant to the European corn borer (CB) achieved significant success as a single trait by the early 2000s, and the GT trait, which came slightly later, ultimately became the most widely adopted GE trait in corn (>90% by the end of the sample). The root worm (RW) trait—which conferred resistance to various species of root worms and was almost exclusively marketed and adopted in stacked trait varieties—was the last trait introduced (2004). Following 2004, the corn market rapidly shifted to the adoption of stacked trait varieties. By 2010, stacked varieties accounted for more than 65% of the market, a number which further increased to roughly 83% of the market by 2016. Notably, the RW trait peaked at just over 50% in 2013 and subsequently fell to just under 46% in 2016. By 2016, farmers had adopted the corn GT trait on roughly 92% of acres and CB trait on approximately 83% of acres.

Table 2. Adoption Rates for US Corn and Soybeans, 1996-2016

	Soybeans	Corn Single Traits			Corn Stacked Traits				Corn
Year	GT	GT	CB	RW	GT-CB	GT-RW	CB-RW	GT-CB-RW	GE
1996	2.3%	0.0%	0.7%	0.0%	0.0%	0.0%	0.0%	0.0%	0.7%
1999	51.4%	2.5%	20.8%	0.0%	0.0%	0.0%	0.0%	0.0%	23.4%
2002	80.7%	7.2%	23.9%	0.0%	2.2%	0.0%	0.0%	0.0%	33.2%
2004	86.6%	12.7%	24.6%	1.0%	7.3%	0.6%	0.1%	0.0%	46.2%
2007	95.0%	18.1%	14.7%	0.6%	20.5%	2.1%	2.9%	18.3%	77.1%
2010	94.2%	20.2%	2.1%	0.0%	14.8%	0.4%	1.1%	50.0%	88.6%
2013	93.0%	13.4%	0.6%	0.0%	26.0%	0.6%	0.2%	51.8%	92.6%
2016	87.5%	8.9%	0.1%	0.0%	38.0%	0.0%	0.0%	45.5%	92.5%

Note: this table reports adoption rates for GE traits, computed as % of planted acres, for selected years over the period 1996-2016. Source: Authors' calculation based on Kynetec data.

3.3 GE Trait Licensing

The market share data in **Table 1** provide information about concentration in the product market. As discussed in the foregoing, however, ownership and licensing of GE traits provide another layer of interest for this industry. For soybeans, there is only one commercial GE trait of interest, GT, developed by Monsanto. For corn traits, Monsanto also played a leading role, but commercially-viable GE traits from other firms are also available in corn varieties sold to farmers. **Table 3** provides GE market shares (% of planted GE acres), by licensee and licensor, for three time intervals. For the purposes of this table, we fractionally assign traits owned by multiple firms, in equal share, to each co-owner.[6]

Table 3. Licensee by Licensor Shares in US Corn, Selected Years

Licensee → Licensor ↓	Monsanto	Dow	Dupont	Syngenta	AgReliant	Other	Total
				2002-2006			
Monsanto	**24.66%**	2.78%	24.61%	2.77%	3.31%	25.82%	84.0%
Dow	0.04%	**0.60%**	2.21%	0.04%	0.00%	0.29%	3.2%
Dupont	0.04%	0.60%	**2.21%**	0.04%	0.00%	0.29%	3.2%
Syngenta	0.00%	0.00%	0.02%	**9.64%**	0.00%	0.01%	9.7%
				2007-2011			
Monsanto	**37.20%**	2.69%	13.10%	1.56%	6.53%	12.60%	73.7%
Dow	0.92%	**0.76%**	7.43%	0.10%	0.04%	0.79%	10.0%
Dupont	0.06%	0.60%	**7.43%**	0.10%	0.01%	0.73%	8.9%
Syngenta	0.01%	0.05%	0.13%	**6.16%**	0.02%	0.97%	7.3%
				2012-2016			
Monsanto	**30.01%**	2.76%	13.40%	0.05%	6.44%	9.28%	61.9%
Dow	6.54%	**1.79%**	9.01%	0.00%	0.54%	1.75%	19.6%
Dupont	0.00%	0.19%	**9.01%**	0.00%	0.00%	0.63%	9.8%
Syngenta	0.00%	0.27%	0.26%	**6.40%**	0.01%	1.67%	8.6%

Note: Each entry identifies the market share (% of GE planted acres) for each licensee-licensor combination for each of the three given sub-periods. Source: Authors' calculation based on Kynetec and ISAAA data.

[6] For example, we assign ownership of the triple-stack GT-CB-RW embedded in varieties of the Herculex line developed by Dow and DuPont, which includes Monsanto's GT trait, equally to the three firms (one-third each).

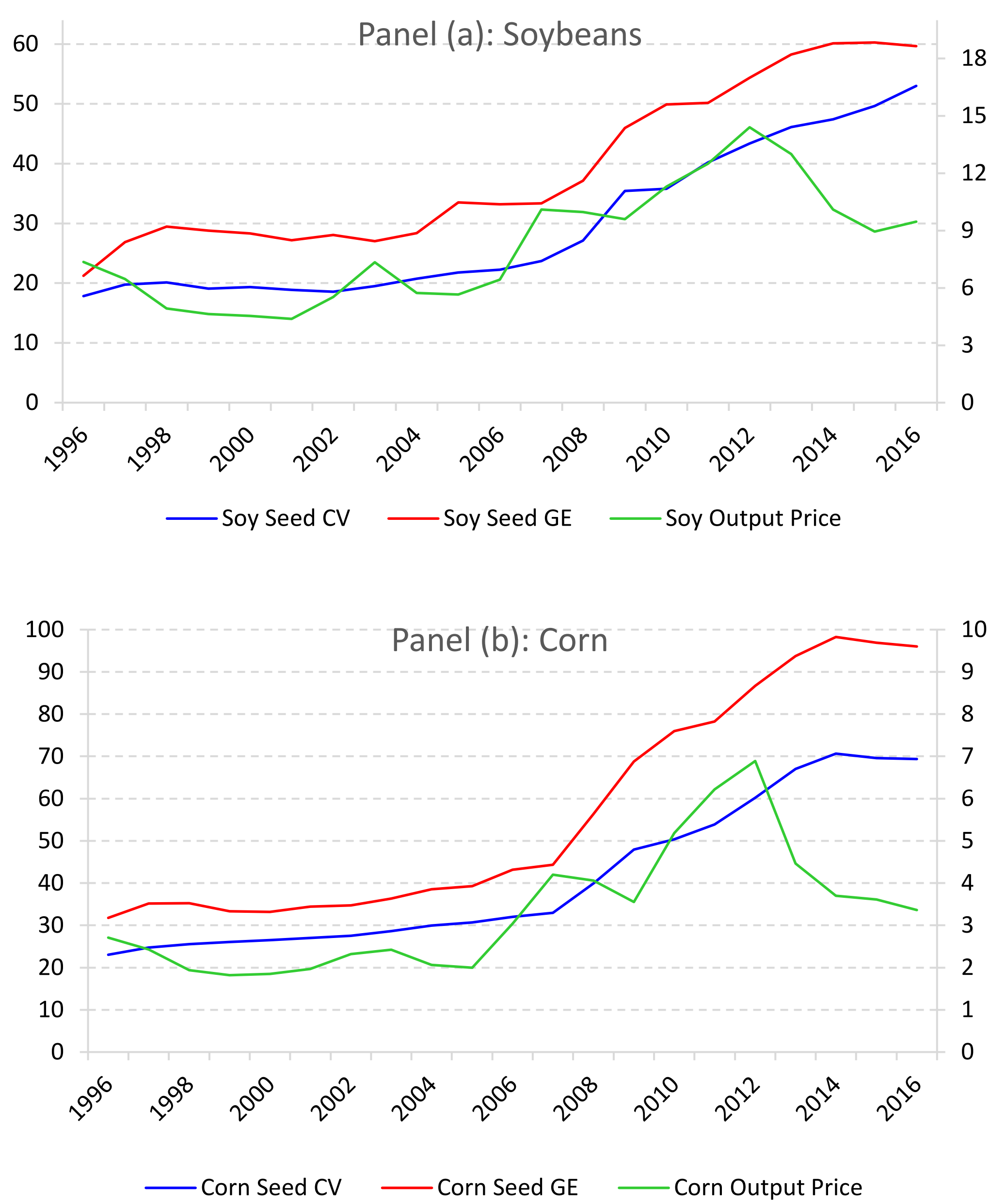
Table 3 identifies both the size of each licensee in the product market (GE corn seed) and the size of each licensor in the GE trait market. For example, GE seed sold by DuPont that contained Monsanto GE traits comprised 24.61% of the GE corn seed market in the 2002-2006 period. Summing the entries for a given row identifies the total share of GE corn acres that embed traits from that licensor, whereas summing the shares for a given column identifies the seed market share for the corresponding licensee. For example, during the 2002-2006 period, Monsanto was the GE licensor of about 84% of planted GE acres, whereas it was the final seller of about 24.7% of the market.

Table 3 illustrates a few stylized facts. First, Monsanto was the leading licensor in all three periods, accounting for 84%, 74%, and 62% of the GE trait market in the 2002-2006, 2007-2011, and 2012-2016 periods, respectively. Second, some licensees rely heavily on their own traits, whereas others almost entirely rely on traits from other companies. Monsanto and Syngenta primarily sell GE seed that embed their own GE traits, whereas Dow, DuPont, AgReliant, and other companies primarily source their traits from Monsanto. This reliance has decreased over time, however. By the 2012-2016 period, Dow and DuPont together accounted for nearly 30% of the GE trait market, with even Monsanto now sourcing certain GE traits from Dow.

3.4 Corn and Soybean Seed Prices

Concerns about rising market power and the potential impacts of cross-licensing by US seed firms have centered around rising nominal seed prices. From 1996 to 2016, *all* seed prices rose markedly, including non-GE prices. In soybeans, GT and non-GT prices increased by roughly 300%, and similar price increases occurred in the corn seed market (**Figure 1**). Generally, the absolute gap between non-GE and GE prices (the GE premium) also increased. For soybeans, the GT premium was initially around $4/acre in 1996, increased to a peak of $15/acre in 2010, and shrunk noticeably to $6.48/acre in 2016. The rising problem of glyphosate weed resistance, which reduced the efficacy of GT varieties, can perhaps explain this final decrease. The GE premium in corn also grew significantly, from just $6.30/acre in 1996, to more than $30/acre in 2016. Most of this increase, however, reflects the adoption of stacked trait varieties. For example, the premium for single-trait GT corn increased from around \$5/acre in 1998 to a high of nearly \$17/acre in 2010, and then fell to roughly \$10/acre in 2016. See Appendix B for more details.

Figure 1. Seed and Output Prices, 1996–2016



Note: Panel (a) charts the average soybean seed prices (\$/acre, left axis) for conventional and GE varieties, and the average output price received by farmers (\$/bu, right axis). Panel (b) charts the average corn seed prices (\$/acre, left axis) for conventional and GE varieties, and the average output price received by farmers (\$/bu, right axis). Average seed prices are computed from Kynetec data, output prices (marketing year) are from USDA-NASS.

What are the root causes of this general rise in seed prices? In the case of conventional seed products, there were only slight improvements in quality, certainly not enough to explain their multifold increase. The trend in crop output prices, which affect demand and seed production costs, likely played a critical role.

Figure 1 also reports the output prices for soybeans and corn. From 2007–2012, there were major increases in corn and soybean output prices, on the order of 200%. These increases would have impacted farmers' demand for all inputs (including seeds) and also led to higher seed production costs (because seed firms contract with individual farmers to grow commercial seed), both of which likely contributed to higher seed prices. However, output prices fell significantly from 2013–2016, albeit remaining elevated relative to pre-2007 levels. Seed prices, on the other hand, did not fall significantly during this period. This, in turn, raises the question of how much rising concentration and licensing contributed to the sustained increase in seed prices, questions we seek to address below.

4. The Supply Model

We develop a model in which seed firms strategically choose prices for the varieties they sell in a differentiated-product market. A common issue in this setting is that the Nash equilibrium conditions include marginal costs that are typically not observed. The standard solution, from the new empirical industrial organization (Bresnahan 1989), is to use an indirect approach whereby the Nash optimality conditions along with the estimated demand structure recovers the markup of equilibrium prices over (unobserved) marginal costs (Shum 2017). The non-standard feature, in our setting, is the existence of cross-licensing and its role in firms' Nash equilibrium conditions. Unfortunately, little is publicly known about the nature of GE trait licensing (such contracts are typically confidential). Following Armstrong (1999), we expect that licensing the GE trait via a flat fee would not be profitable for a firm. As in Weeds (2016), however, licensing via a per-unit fee should improve the profit of the licensor. The critical insight here is that the royalty rate is equivalent to an increase in the marginal cost for licensees, but it also constitutes an additional "opportunity cost" for the licensor. Thus, this theoretical perspective strongly suggests that licensors will prefer per-unit royalties. Accordingly, our baseline model assumes that firms charge per-unit royalties, and that the level of these royalties are pre-determined vis-à-vis the firms' seed price choices. Still, of course, we do not observe the level of these royalties, but we can adapt the standard empirical strategy to our setting.

To deal with the fact that we do not observe royalties, we exploit a unique feature of the corn and soybean seed market—unlike products such as cars (widely studied in the empirical I.O. literature), we can presume the manufacturing marginal cost of producing an additional unit of seed is approximately the same across different varieties (of the same crop) within a given firm. More details on the rationale for this assumption are explained in Appendix C. Note that such marginal production costs exclude GE royalties (which we discuss next) as well as the underlying R&D costs (presumed sunk by the time firms price their commercial varieties).

4.1. A Motivating Example

Suppose there are only two seed firms, labeled A and B, and only one GE trait, which firm A owns and licenses to firm B. Each firm sells both a conventional variety (subscript 0) and a GE variety (subscript 1), so that there are four total seed products on the market. Let p_j^f denote the price of variety type $j \in \{0,1\}$ sold by firm $f \in \{A, B\}$, and let $Ms_j^f(\mathbf{p})$ represent the demand functions for each product, where M denotes market size, $s_j^f(\mathbf{p})$ is market share of product j, and $\mathbf{p}$ is vector of all market prices. Thus, the profit functions for each firm are given by

$$\Pi^A = M[(p_0^A - mc^A)s_0^A + (p_1^A - mc^A)s_1^A + rs_1^B]$$
$$\Pi^B = M[(p_0^B - mc^B)s_0^B + (p_1^B - mc^B - r)s_1^B]$$

where mc^f is the marginal production cost, and r is the per-unit royalty charged by firm A. Accordingly, the *overall* marginal cost of producing an additional unit of soybeans is mc^A for both of firm A's varieties, mc^B for firm B's conventional variety, and $(mc^B + r)$ for firm B's GE variety. Also note that the royalty revenue that A receives from B is $rs_1^B M$. Each firm chooses the price for each product it sells that maximizes profit. The firms' best-response functions satisfy the following first-order conditions:

$$s_0^A + \left(p_0^A - mc^A\right)\frac{\partial s_0^A}{\partial p_0^A} + (p_1^A - mc^A)\frac{\partial s_1^A}{\partial p_0^A} + r\frac{\partial s_1^B}{\partial p_0^A} = 0$$

$$s_1^A + \left(p_0^A - mc^A\right)\frac{\partial s_0^A}{\partial p_1^A} + (p_1^A - mc^A)\frac{\partial s_1^A}{\partial p_1^A} + r\frac{\partial s_1^B}{\partial p_1^A} = 0$$

$$s_0^B + (p_0^B - mc^B)\frac{\partial s_0^B}{\partial p_0^B} + (p_1^B - mc^B - r)\frac{\partial s_1^B}{\partial p_0^B} = 0$$

$$s_1^B + (p_0^B - mc^B)\frac{\partial s_0^B}{\partial p_1^B} + (p_1^B - mc^B - r)\frac{\partial s_1^B}{\partial p_1^B} = 0$$

With the exception of the royalty terms, these conditions are standard to a Bertrand differentiated-product pricing model. Both firms set their prices taking into account marginal costs, as well as the impact of those prices on the demand for the other products they sell. The novelty introduced by licensing is that the licensee bears an additional direct per-unit cost (the royalty) for the GE product it sells, and the licensor has an additional (opportunity) cost associated with its pricing choice—aggressive pricing can increase its market share, but leads to lost license revenue. Both of these effects will tend to raise equilibrium prices (relative to what would occur without per-unit royalties).

On the issue of identification, the above first-order conditions show that we can separately identify royalty rates because they add to the marginal production cost of the licensee's (firm B) GE variety but not to the marginal cost of its conventional variety (and, absent royalties, we presume the marginal production cost of the two varieties is the same). And, for the licensor (firm A), royalties define an opportunity cost term—aggressive pricing of their own product would decrease the sales of their competitor and, given substitutability, reduce royalty revenues.

4.2. A More General Pricing and Licensing Model

As in the foregoing, we continue to presume that licensing involves per-unit royalties. The additional features that we allow for is that a firm may sell multiple products (with and/or without GE traits), may own multiple GE traits, and some GE traits may be owned by multiple firms. As discussed earlier, many seed products, especially the most recent ones, include so-called "stacked traits." It is important to understand that producers cannot stack traits arbitrarily; and, as a major legal case between Monsanto and DuPont clearly illustrates, contractual restrictions govern how and who can do the trait stacking (Stuart 2013). Furthermore, some stacked traits are the result of research joint ventures between otherwise competing seed companies. To derive as flexible a licensing model as possible, we treat stacked traits as one distinct licensable item. Hence, by construction, a product in our setting either does not contain GE traits (i.e., conventional seed products) or contains one "trait" (possibly a bundle of individual GE traits).

Bertrand-Nash with Royalties

In a given market, F denotes the set of firms (seed companies) (and, with some abuse of notation, also the number of firms), J^f denotes the set of products sold by firm $f \in F$, and, J denotes the set of all products sold in this market. Our modeling framework continues to maintain the assumption of per-unit royalties for licensed GE traits (some of which are stacked traits). At this stage we do not presume that a licensor would charge the same royalty, for a given trait, to all licensees (although this condition will be maintained in the empirical application). As noted, because of how we handle stacked traits, we include only one GE trait in a given GE product. A product is, by definition, owned only by one firm. Hence, a general way of reflecting licensee-licensor bargaining positions is to make royalties "product specific." That is, without loss of generality, we can think of only one royalty rate per GE product, denoted r_j. This formulation thus results in a $J \times 1$ vector of (market-specific) royalty rates.

In our setting it is essential to keep track of trait ownership distinctly from product ownership. The sets J^f account for the latter at this stage. As for the former, we define the $J \times 1$ firm-specific trait-product ownership vectors $\mathbf{z}^f$ whose elements z_i^f denote the fraction of the GE trait included in product i owned by firm f. So, we can write the profit function for firm f in this market as:

$$\Pi^f = M\left[\sum_{j \in J^f}\left(p_j - c_j - \sum_{k \neq f \in F} z_j^k r_j\right)s_j(\mathbf{p}) + \sum_{i \notin J^f} z_i^f r_i s_i(\mathbf{p})\right] \tag{1}$$

where M is the size of the market; c_j denotes the firm's marginal cost for product j; and, s_j denotes the market share of product j. Here, the terms that involve the royalty rates r_i are the additional elements that arise because of licensing, relative to the standard Nash-in-prices equilibrium conditions (e.g., Nevo 2001).

By construction, the number of licensing arrangements (royalty rates) cannot exceed the number of products (because, again, each product contains at most one GE trait). But this number will be strictly less than the number of products because firms may wholly own the GE trait they use, and also because conventional seed products do not include any GE trait. Just how many non-zero royalty rates there are in any one market depends on the extent to which firms use traits they do not own. In the foregoing, we capture the combination of trait ownership and trait inclusion by the vectors $\mathbf{z}^f$. To compute the number of rates that need to be tracked requires explicit consideration of the interaction between trait and product ownership. The firm-specific sets J^f, defined earlier, reflect the latter. An equivalent primitive representation of such ownership is by the firm-specific $J \times 1$ vector $\boldsymbol{\omega}^f$, where $\boldsymbol{\omega}_j^f = 1$ if firm f owns product j (i.e., $j \in J^f$) , and $\boldsymbol{\omega}_j^f = 0$ otherwise. From this formulation we can also construct the $J \times J$ block-diagonal product ownership matrix (e.g., Nevo 2001), which can be obtained as the sum of outer products: $\mathbf{H} \equiv \sum_{f \in F} \boldsymbol{\omega}^f \left[\boldsymbol{\omega}^f\right]'$. Note that, by construction, $\mathbf{H}_{ij} = 1$ iff the same firm owns products j and i, and $\mathbf{H}_{ij} = 0$ otherwise.

Next, we define the $J \times 1$ vector $\mathbf{z} \equiv \sum_{f \in F} \mathbf{z}^f$. Note that this is just a vector of indicator variables with element $z_j = 1$ if product j is a GE product, and $z_j = 0$ if product j is a conventional product. We can now define the $J \times 1$ vector $\mathbf{x}$ as:

$$\mathbf{x} \equiv \mathbf{z} - \sum_{f \in F} diag\left(\boldsymbol{\omega}^f\right)\mathbf{z}^f \tag{2}$$

By virtue of this definition, therefore, the elements x_j of this vector denote the fraction of the GE trait embedded in product j that is ***not*** owned by the firm that sells product j. Note that the number of royalty-bearing transactions in this market is the number of non-zero elements in the vector $\mathbf{x}$.

Given the foregoing, we can rewrite the objective function of firm f in (1) as:

$$\Pi^f = M\left[\sum_{j \in J^f} \left(p_j - c_j - x_j r_j\right) s_j(\mathbf{p}) + \sum_{i \notin J^f} z_i^f r_i s_i(\mathbf{p})\right] \tag{3}$$

Again, the presumption is that firms maximize profit by setting prices, conditional on previously-negotiated royalty rates, and an exogenous ownership of products and traits.

Differentiating with respect to p_j gives the profit-maximizing condition for product j:

$$s_j + \sum_{\ell \in J^f} \frac{\partial s_\ell}{\partial p_j}(p_\ell - c_\ell) - \sum_{\ell \in J^f} \frac{\partial s_\ell}{\partial p_j} x_\ell \, r_\ell + \sum_{i \notin J^f} \frac{\partial s_i}{\partial p_j} z_i^f r_i = 0, \quad j \in J^f, \ \ \forall j, i \in J \tag{4}$$

The optimality conditions (4) illustrate the fact that GE trait royalties add two sets of terms, relative to the standard Bertrand-Nash conditions. First, for licensees, having to pay royalties adds to the marginal costs of products sold. The term x_ℓ tracks this effect and denotes the fraction of the GE trait embedded in product ℓ that the firm selling the product does not own. Second, for licensors, royalties are a source of revenue, which is proportional to the amount of product sold by competitors who use GE traits owned by the firm. This effect is tracked by z_i^f, the fraction of the GE trait included in product i that is owned by the firm selling product j.

Royalties and equilibrium prices

For the purpose of the empirical application that follows, it is useful to write the Bertrand-Nash optimality conditions in (4) in matrix notation. Let $\mathbf{S}(\mathbf{p})$ denote the $J \times J$ matrix of substitution effects, with elements $S_{j\ell} \equiv \partial s_\ell / \partial p_j$. Then, following Nevo (2001), we define a matrix that combines product ownership information with substitution effects: $\boldsymbol{\Omega} \equiv -\mathbf{S} \circ \mathbf{H}$. The matrix $\boldsymbol{\Omega}$ is the (negative of) the element-by-element product of the substitution effects and ownership matrices, both of dimension $J \times J$ (the symbol $\circ$ denotes the *Hadamard product* of two matrices of the same dimension, such that $\Omega_{ij} \equiv -H_{ij} \cdot S_{ij}$). Furthermore, it is useful to define the following firm-specific matrices:

$$\boldsymbol{\Omega}^f \equiv -diag(\boldsymbol{\omega}^f)[\mathbf{1}_{J \times J} - \mathbf{H}] \circ \mathbf{S} \tag{5}$$

These are $J \times J$ matrices with typical element $\Omega_{ij}^f = -\partial s_i / \partial p_j$ if $i \in J^f$ and $j \notin J^f$, and $\Omega_{ij}^f = 0$ otherwise (including $\forall i \notin J^f$).

Given the foregoing, we can express the Bertrand-Nash conditions in matrix form as:

$$\mathbf{s}(\mathbf{p}) - \boldsymbol{\Omega}(\mathbf{p})[\mathbf{p} - \mathbf{c}] + \boldsymbol{\Omega}(\mathbf{p}) \cdot diag(\mathbf{x}) \cdot \mathbf{r} - \sum_{f=1}^{F} \boldsymbol{\Omega}^f(\mathbf{p}) \cdot diag\left(\mathbf{z}^f\right) \cdot \mathbf{r} = 0 \tag{6}$$

where $\mathbf{s}$, $\mathbf{p}$, $\mathbf{c}$, and $\mathbf{r}$ denote the vectors of shares, prices, marginal costs, and royalty rates, respectively (all are $J \times 1$ vectors). The pricing condition from (6) is:

$$\mathbf{p} = \mathbf{c} + \boldsymbol{\Omega}^{-1}\mathbf{s} + diag(\mathbf{x})\,\mathbf{r} - \boldsymbol{\Omega}^{-1} \sum\nolimits_{f=1}^{F} \Omega^f diag\left(\mathbf{z}^f\right) \mathbf{r} \tag{7}$$

Note that this pricing equation, for the special case when there are no GE licensing arrangements ($\mathbf{x} = \mathbf{0}$ and $\mathbf{r} = \mathbf{0}$), reduces to $\mathbf{p} = \mathbf{c} + \boldsymbol{\Omega}^{-1}\mathbf{s}$ (i.e., the standard Bertrand-Nash pricing conditions) (e.g., equation (1) in Nevo 2001).

5. The Demand Model

The demand side of the corn and soybean seed market is based on Ciliberto, Moschini and Perry (2019), who develop and estimate a discrete-choice model of seed demand at the farm level. The unit of observation is a purchase instance that identifies the specifics of the seed variety purchased (including the brand, the identity of each the included GE traits, the price paid, the amount purchased and the land size of the plot planted with the purchased seed). The presumption of the discrete choice framework we adopt is that farmers select the seed variety that, in the choice set available to them, yields the highest expected profit. We observe these choices in $m = 1, \ldots, N_m$ markets for $i = 1, \ldots, I_m$ plots, where a market is defined as a year-CRD combination. We denote the set of products available to a farmer in market m as J_m, and T denotes the set of available GE traits.

The profit per acre associated with variety j on plot i in market m takes the form:

$$\pi_{ijm} = \sum_{\tau \in \mathrm{T}} \gamma_{\tau m} D_{j\tau} - p_{jm} + \xi_{c,t} + \xi_{c,l} + \xi_{c,b} + \xi_{jm} + \nu_{ijm} \tag{8}$$

where $D_{j\tau}$ is a dummy variable equal to 1 if variety j contains GE trait τ; p_{jm} is the market-specific price (seed cost per acre) of variety j; and, $\xi_{c,t}$, $\xi_{c,l}$, and $\xi_{c,b}$ are, respectively, crop-time, crop-region, and crop-brand fixed effects. The subscript notation is as follows: c and b identify the crop (corn or soybeans) and brand (e.g., Asgrow), respectively, associated with seed variety j; and, t

and l identify the year and CRD (location), respectively, associated with market m. The error term ξ_{jm} captures unobserved product-market-specific factors that impact the mean profit per acre for farmers in market m.

The final term ν_{ijm} captures unobserved plot-specific variation in the return to different seed products. Following Verboven (1996) and Björnerstedt and Verboven (2016), we assume ν_{ijm} is distributed according to the two-level nested-logit model. The upper level, denoted by $g \in \{0,1\}$, consists of the outside option ($g = 0$), and the inside option (the set of all corn and soybean seed varieties) ($g = 1$). We further partition corn and soybean seeds into their own separate subgroups: $h = 1$ denotes corn products; and, $h = 2$ denotes soybean products. By specifying ν_{ijm} in this way, we aim to capture the rotation effect between corn and soybeans. Indeed, the rotation effect implies that, for a given plot, if the return to a soybean product is high, then it is more likely for the return to other soybean products to also be high.

Given these assumptions, we can write the plot-specific error as:

$$\nu_{ijm} = \varepsilon_{igm} + (1-\sigma_2)\varepsilon_{ihm} + (1-\sigma_1)\varepsilon_{ijm}$$

where ε_{igm}, ε_{ihm}, and ε_{ijm} possess distributions such that ε_{igm}, $(1-\sigma_2)\varepsilon_{ihm} + (1-\sigma_1)\varepsilon_{ijm}$, and $\varepsilon_{igm} + (1-\sigma_2)\varepsilon_{ihm} + (1-\sigma_1)\varepsilon_{ijm}$ have the Type I extreme value distribution (Verboven 1996). The parameters σ_1 and σ_2 capture the degree to which the unobserved returns to seed varieties within the same group and subgroup, respectively, are correlated. For the model to be consistent with profit maximization, it is necessary that $0 \le \sigma_2 \le \sigma_1 \le 1$ (McFadden 1978).

From these distributional assumptions, the standard market level estimating equation for the two-level nested logit model is written as (Verboven and Björnerstedt 2016):

$$\ln\left(\frac{s_{jm}}{s_{0m}}\right) = \mathbf{q}_j\boldsymbol{\theta}_m - \alpha p_{jm} + \sigma_1 \ln\left(\frac{s_{jm}}{S_{hgm}}\right) + \sigma_2 \ln\left(\frac{S_{hgm}}{S_{\mathrm{g}}}\right) + \xi_{jm} \tag{9}$$

where s_{jm}, s_{0m}, S_{hgm}, and S_{gm}, are observed shares—respectively, the share of variety j, the share of the outside option, the subgroup share of crop h (corn or soybeans) within the inside option, and the observed group share of the inside option (corn plus soybean seeds), are all specific to market m. Here the vector $\mathbf{q}_j$ denotes trait-specific attributes of seed variety j, and the coefficient on the price variable, α, is the reciprocal of the unidentified scaling parameter of logit models (Train 2009).

To address the well-known issue price of endogeneity, as well as the endogeneity of the nested logit variables, we use characteristic-based instruments (Berry, Levinsohn, and Pakes 1995). Following Ciliberto, Moschini, and Perry (2019), we generate counts for the total number of competing products (irrespective of GE traits) by: market; market and brand; market and parent company; market and crop; market, brand, and crop; and, market, parent company, and crop. We then compute the same variables for each of the three GE traits, plus non-GE products: GT, CB, RW, and non-GE. This results in 30 instrumental variables.

6. Results

Our empirical analysis proceeds in two stages. First, we estimate the seed demand model. This provides us with the critical demand elasticities that characterize the Bertrand-Nash equilibrium markups. Next, we use the pricing equations with royalties and cross-licensing agreements to estimate marginal costs and royalty rates.

6.1. Seed Demand

Table 4 contains the estimated demand parameters for the two-level nested-logit model. It also contains the implied willingness-to-pay (WTP) values for each of the period-specific GE traits, which we discuss further below. Following the main specification in Ciliberto, Moschini, and Perry (2019), we permit each of the GE trait coefficients to differ across time. However, because the data now extends to 2016, we have added one additional time interval for each GE trait (202016). Overall, the coefficients accord with expectations. The price coefficient is negative and significant, and the nested logit coefficients have the correct ordering. That is, products within the same subgroup (crop), captured by σ_1, are closer substitutes than products within the same group (corn *or* soybeans), measured by σ_2. The GE trait coefficients are generally positive and statistically significant. The exceptions are the corn GT and RW trait coefficients in the first time intervals; however, they are not statistically different from zero.

Table 4. Estimated Demand Coefficients and WTPs

	Coefficient	Standard error	WTP ($/acre)	Standard error
Price	-0.0174	0.0012		
σ_1	0.8428	0.0084		
σ_2	0.4728	0.0520		
Soy GT (1996–2000)	0.2640	0.0225	15.18	0.73
Soy GT (2001–2006)	0.3999	0.0246	23.00	1.06
Soy GT (2007–2011)	0.4005	0.0270	23.03	1.44
Soy GT (2012–2016)	0.3046	0.0218	17.51	1.18
Corn GT (1996–2000)	-0.0114	0.0302	-0.66	1.76
Corn GT (2001–2006)	0.0528	0.0163	3.03	0.80
Corn GT (2007–2011)	0.2788	0.0200	16.03	0.55
Corn GT (2012–2016)	0.2659	0.0220	15.29	0.77
CB (1996–2000)	0.1003	0.0214	5.77	1.00
CB (2001–2006)	0.0787	0.0162	4.53	0.72
CB (2007–2011)	0.1961	0.0172	11.27	0.63
CB (2012–2016)	0.2926	0.0286	16.83	1.48
RW (2001–2006)	0.0282	0.0244	1.62	1.33
RW (2007–2011)	0.2606	0.0192	14.98	0.59
RW (2012–2016)	0.1513	0.0166	8.70	0.57
STACK (1996–2000)	0.0279	0.0931	1.60	5.37
STACK (2001–2006)	-0.0146	0.0174	-0.84	0.98
STACK (2007–2011)	-0.1216	0.0163	-6.99	0.85
STACK (2012–2016)	-0.0302	0.0271	-1.74	1.55
Elasticities:				
Own	-6.4538			
Cross: within crop	0.2480			
Cross: across crop	0.0363			
Cross: outside option	0.0139			
N	89,088			
GR^2	0.923			

Note: Table 4 provides the estimation results for the two-level nested-logit model with instrumental variables for the price variable. The model includes crop by year, crop by brand, and crop by CRD fixed effects. GR^2 is the generalized measure of fit for models with instrumental variables, as suggested by Pesaran and Smith (1994).

The third and fourth columns in **Table 4** provide the implied WTPs ($/acre) and associated standard errors for each of the GE traits in the respective time interval. The WTPs were obtaining by dividing each GE trait coefficient by the price coefficient (Train 2009). In the case of the soy GT trait, farmers' WTP initially increases from $15.36/acre to $25.07/acre, remains at a similar level in the third time interval ($25.50/acre), and then decreases to $19.70/acre in the 2012–2016 period. The decrease in the final interval is likely to due to the emergence of glyphosate weed resistance, which reduced the efficacy of GT soybeans, causing some farmers to shift back to non-GT soybeans varieties. The values associated with the corn GT trait exhibit a similar temporal pattern, but are smaller in value, perhaps owing to the fact that there are more available herbicide options for weed control in corn (e.g., atrazine). Farmers' WTP for the CB trait increased from the second period to the third, and again in the fourth, reaching $17.66/acre. By contrast, the RW trait reached its peak valuation in the third time interval (2007–2011) at $15.66/acre and then nearly halved to $8.41/acre in the final period. Here again, resistance issues were likely the main driver behind the falling value of the RW trait. The prevailing consensus is that the insects targeted by the RW trait quickly adapted, reducing its efficacy.

Finally, the STACK coefficients, which capture whether there was sub- or super-additivity in the value of multiple traits, indicates there was sub-additivity in the third time interval, but in all other periods, the coefficients were not statistically different from zero. This implies that, most of the time, the value of seed embedding multiple GE traits was roughly the sum of values associated with each individual trait.

Given the similarity in data and model structure to Ciliberto, Moschini, and Perry (2019), we can also make some comparisons with respect to the WTP values. Overall, the magnitudes and temporal patterns for the GE trait values are very similar. For example, in Ciliberto, Moschini, and Perry (2019) the estimated WTPs for the soy GT trait were $16.88/acre (1996–2000), $23.96/acre (2001–2006), and $25.69/acre (2007–2011). The values obtained here are all within $2/acre of those estimates, and the similarities extend to the estimated values for all other traits. As noted, however, Ciliberto, Moschini, and Perry (2019) did not include data from 2012–2016; and, as discussed above, there were some notable changes that took place during this period.

The last components provided in **Table 4** are the mean own and cross price elasticities. The mean own price elasticity is about -6.45, which is consistent with profit maximization by differentiated-product firms. The cross-price elasticities demonstrate farmers' tendency to substitute between varieties of the same crop, rather than switch crops, and they are in turn more likely to substitute between corn and soybeans, rather than switch to some outside alternative.

6.2 Royalty Estimation

For reasons explained in the foregoing, we estimate royalties (and marginal costs) over the period 2002–2016. Over this period, we observe 20 GE traits—again, in our modeling framework we treat stacked traits as an individual trait. In the baseline model, the assumption is that the royalty associated with each trait is the same regardless of the identity of the licensee. Hence, we estimate 20 royalty rates.

The basis for estimating royalty rates is the Bertrand-Nash equilibrium condition in the pricing equation (7). To make this operational, we parameterize firms' marginal costs to depend on both observed variables and unobserved components; that is,

$$\mathbf{c} = \mathbf{D}\boldsymbol{\gamma} + \boldsymbol{\varepsilon} \tag{10}$$

Inserting this parameterization into equation (7) results in the primitive estimating equation for the marginal cost parameters and royalty rates, which we can express as

$$\mathbf{p} = \mathbf{D}\boldsymbol{\gamma} + \boldsymbol{\Omega}^{-1}\mathbf{s} + (\mathbf{X} \;\; + \mathbf{Z}\,)\mathbf{r} + \boldsymbol{\varepsilon} \tag{11}$$

where $\mathbf{X} \equiv diag(\mathbf{x})$ and $\mathbf{Z} \equiv -\boldsymbol{\Omega}^{-1}\sum_{f=1}^{F}\Omega^{f}\,diag(\mathbf{z}^{f})$. Here, if n is the number of product-market observations ($n = 71{,}081$ in our case), then the vectors $\mathbf{p}$ and $\mathbf{s}$ are of dimension $n \times 1$, while the matrices $\boldsymbol{\Omega}$, $\mathbf{X}$, and $\mathbf{Z}$ are $n \times n$. Consequently, the vector of royalties $\mathbf{r}$ is $n \times 1$. When we estimate the royalty rates, we impose the restriction that the same trait commands the same royalty for all products that contain it. That is, the vector of royalties $\mathbf{r}$ is expressed in terms of k royalty rates, captured by the vector $\boldsymbol{\beta}$ ($k = 20$ in our case). Thus, we write $\mathbf{r} = \mathbf{W}\boldsymbol{\beta}$, where $\mathbf{W}$ is an $n \times k$ matrix that codes for the maintained restrictions.

For the purpose of estimation, we define the left-hand side variable $\mathbf{y} \equiv \mathbf{p} - \boldsymbol{\Omega}^{-1}\mathbf{s}$, such that we can rewrite equation (11) as

$$\mathbf{y} = \mathbf{D}\boldsymbol{\gamma} + (\mathbf{X} + \mathbf{Z})\mathbf{W}\boldsymbol{\beta} + \boldsymbol{\varepsilon} \tag{12}$$

This is a linear regression on known variables (based on the fitted demand model) that estimates the vector of marginal costs parameters $\boldsymbol{\gamma}$ and the vector of royalty rates $\boldsymbol{\beta}$. Note, however, that the variables that enter the matrix $\mathbf{Z}$ are computed based on the estimated demand parameters and the observed prices/shares. Such terms on the right-hand side of the equation are endogenous because price is likely correlated with the unobserved component of MCs. The structure of the problem at hand, however, provides a simple and elegant solution to this issue because the matrix $\mathbf{X}$ is fully exogenous (under our assumptions). This suggests the following iterative procedure:

- Define a vector of starting values for the royalties, denoted $\boldsymbol{\beta}^0$
- Define the left-hand side variable for the ith iteration as $\mathbf{y}^i \equiv \mathbf{p} - \boldsymbol{\Omega}^{-1}\mathbf{s} - \mathbf{ZW}\boldsymbol{\beta}^{i-1}$, $i = 1,2,\dots$
- Estimate $\boldsymbol{\beta}^i$ (and $\boldsymbol{\gamma}^i$) by OLS from $\mathbf{y}^i = \mathbf{D}\boldsymbol{\gamma} + \mathbf{XW}\boldsymbol{\beta} + \boldsymbol{\varepsilon}$
- Iterate until convergence (i.e., the distance between vectors $[\boldsymbol{\beta}^i, \boldsymbol{\gamma}^i]$ and $[\boldsymbol{\beta}^{i-1}, \boldsymbol{\gamma}^{i-1}]$ is less than a given tolerance level)

Concerning the parameterization of marginal costs, we want to account for some relevant heterogeneity across products. The seed products we consider are distinct across two crops (soybeans and maize) and two types (conventionally bred and genetically engineered). In Supplementary Appendix B, we discuss the seed production process in more detail and show that, for both soybeans and maize, it involves three main stages: (*a*) The R&D phase, where breeders develop germplasm with desirable attributes. The output of this phase is so-called "breeder seed," from which we can trace all commercial seed sold to farmers. (*b*) The multiplication of breeder seed into larger quantities of "foundation" or "parent" seed used for final seed production. (*c*) The production of hybrid and/or certified seed sold directly to farmers. These stages require different specialized expertise, and for most seed companies, a different department carries out each stage. Throughout, quality control and maintenance of adequate genetic purity is essential. The main differences between conventional and GE varieties are at the R&D phase. From the perspective of seed firms, long-run breeding considerations govern most of those activities and entail substantial fixed costs. Starting with breeder seed, however, both conventional and GE seed varieties require the various activities in stage (b) and stage (c), described in the foregoing. This justifies our assumption that the associated costs of the "seed production activities" in these two stages are the same across conventional and GE varieties. Of course, such costs are likely different across crops—stages (b) and (c) are somewhat simpler for soybeans, a self-pollinating plant that reproduces true to type.

Based on the foregoing, we specify marginal costs as follows:

$$c_{jm} = \theta_{crop,f} + \theta_{crop,t} + \varepsilon_{jm}$$

where $crop \in \{corn, soybeans\}$, $\theta_{crop,f}$ are the coefficients of crop-by-firm dummy variables; and, $\theta_{crop,t}$ are the crop-by-year fixed effects. In the data, we specifically identify 17 parent companies selling soybean seeds (plus an aggregate "other" group that includes smaller/regional companies), and 16 parent companies (plus the "other" aggregate) selling maize seeds (there are no publicly-provided seeds for commercial maize hybrids). Thus, with 30 crop-by-year fixed effects, we estimate a total of 63 marginal cost parameters.

Table 5 reports the estimated parameters for equation (12). As expected, estimated marginal costs are higher for maize than for soybean seeds. It is also apparent that, when compared with the corresponding marginal cost estimates, the estimated royalty rates are rather large. For example, the royalty rate for the soybean GT trait is estimated at $10.95/acre, which is about 32% of the soybean marginal cost parameter of ($34.33/acre). For maize, the royalty rates somewhat lower—for the GT trait we find $6.72/acre (Syngenta) and $8.19/acre (Monsanto); and, for the CB trait $6.75/acre (Syngenta), $9.18/acre (Monsanto), and $10.50/acre (Dow-DuPont). It is also apparent that stacked traits—which in our structure we presume are licensed as an individual bundle—command higher royalty rates. The triple stack GT-CB-RW owned by Monsanto and Dow, for example, is estimated to command a royalty rate of $44.95/acre, about 80% of the baseline marginal cost.

Table 5. Estimated Pricing Equation, 2002-2016

	estimate	standard error	trait owner/s	N_0^{GE}†	N_1^{GE}†
Marginal costs ‡					
Soybeans	31.6830	0.5040			
Maize	57.7753	0.3172			
Royalty rates—Soybeans					
GT	10.9430	0.3036	Monsanto	14,274	10,352
Royalty rates—Maize					
GT	9.1755	0.2965	Monsanto	9,674	6749
CB	8.1937	0.2229	Monsanto	3,815	2924
GT–CB	14.6299	0.2733	Monsanto	6,125	3671
CB	6.7538	1.0170	Syngenta	1,150	190
CB	10.4969	0.5133	Dow, Dupont	1,390	1390
RW	16.7608	0.6427	Monsanto	630	492
GT–RW	19.8306	0.6633	Monsanto	772	458
CB–RW	18.8460	0.6759	Monsanto	673	441
GT–CB	21.6707	0.4963	Dow, Dupont, Monsanto	1,973	1973
GT–CB–RW	26.9458	0.2819	Monsanto	6,887	3911
RW	37.8920	2.9847	Dow, Dupont	78	78
CB–RW	23.9011	0.9472	Dow, Dupont	445	445
GT–CB–RW	35.6082	0.4820	Dow, Dupont, Monsanto	2,008	2008
GT–RW	41.1424	1.3765	Dow, Dupont, Monsanto	216	216
GT	6.7233	0.6285	Syngenta	1,631	533
GT–CB	11.2790	0.8767	Syngenta	931	259
CB–RW	16.5406	1.9405	Syngenta	295	51
GT–CB–RW	22.8823	0.5324	Syngenta	2,150	768
GT–CB–RW	44.9594	0.4112	Monsanto, Dow	2,893	2893
Number of product–market observations with GE traits				58,010	39,802
Number of product–market observations in regression		71,091			
R^2		0.627			

Notes: ‡ Marginal cost variables also include crop-by-year fixed effects and crop-specific company dummies. Over the period 2002-2016, the data distinguished 17 parent companies (plus an "Others" group) for soybeans and 16 companies (plus "Others") for maize. Thus, the pricing equation involves a total of 63 marginal cost parameters; the reported marginal cost coefficients pertain to the company group "Others" (see the Supplementary Appendix for the full set of estimates). † N_0^{GE} = Number of product–market observations with a GE trait; N_1^{GE} = Number of GE product–market observations that involve a royalty payment. Marginal costs and estimated royalties are expressed in \$/acre (2011 dollars).

The last two columns of **Table 5** also report the number of product-market observations embedding specific traits of interest (distinguishing total and royalty-bearing observations,[7] which bears on the precision with which we can estimate some of these rates).

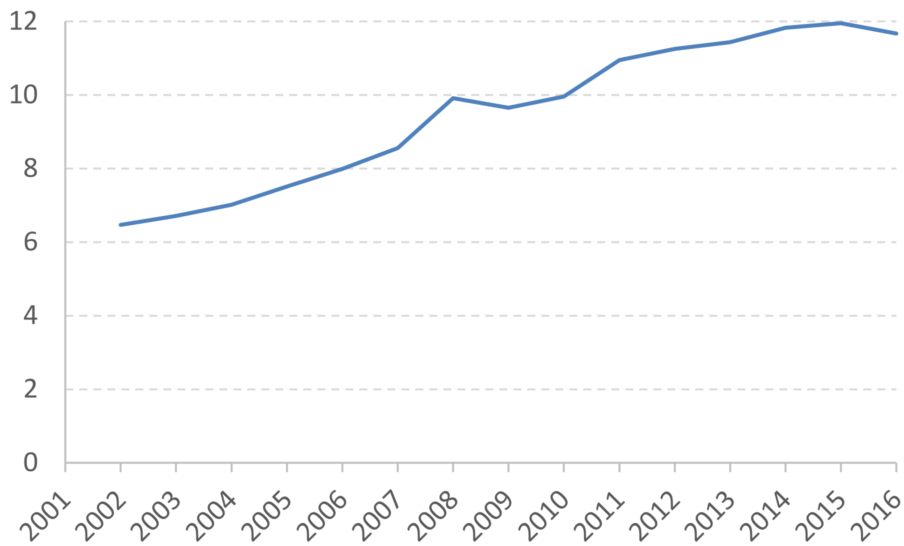
As noted in the foregoing, we estimate the royalty rates (and marginal costs) as constant parameters over the period 2002–2016. We believe this condition is useful for identification, in that it provides a reasonable number of trait-specific observations with licenses (last column of Table 5). How sensible is this assumption, given that licensors and licensees conceivably had opportunities to re-negotiate terms, especially with the introduction of newer and stacked traits? To assess this feature of the model, it is important to understand that we deflate all monetary variables in the model—specifically, we use the crop sector index of prices paid by farmers published by the USDA (index = 1 in 2011). Thus, we express our estimates—for both royalties and marginal costs—in real terms (2011 dollars). Over the 2002–2016 period, farm input prices changed considerably (recall **Figure 1**). Thus, the *nominal* royalty rates implied by the estimates in Table 5 can be reconstructed by using the crop sector index deflator. For example, Figure 2 illustrates the implied nominal royalty rate for the soybean GT trait.

As displayed in **Figure 2**, the estimated model implies rising GT royalty rates over the period of interest, from \$6.50/acre in 2002 to a maximum of about \$12/acre in 2015. A unique institutional feature of the industry provides a window into the real-world relevance of these estimates. Specifically, as noted in section 2, in the early years of commercialization, sales of GE seeds included an explicit "technology fee," separate from the seed price, invoiced separately to farmers to clearly differentiate the GE price premium relative to comparable conventional seed (Carlson, Marra, and Hubbell 1997). For Monsanto's GT soybean trait, this technology fee was originally set at \$5 per bag (roughly equivalent to \$6.20/acre). This fee increased to \$6.50 per bag (about \$8/acre) in the 1998–99 crop year, a level still in place in 2001 when the industry jettisoned the

[7] We do not include, for example, soybean products sold by Monsanto embedding the GT trait in the last column count because Monsanto also owns the GT trait.

technology fee structure in favor of a royalty system. Thus, our estimated nominal royalty rate of \$6.50/acre in 2002 is close to the level suggested by technology fee in place in 2001.[8]

Figure 2. Estimated Nominal Royalty Rate, GT Soybean Trait, 2002–2016



Note: The lowest estimate is of \$6.47/acre (for year 2002) and the largest estimate is \$11.95/acre (for year 2015).

6.3 Licensing Royalties and Seed Prices

Some initial insights into the quantitative importance of licensing for seed prices at the farm level can be constructed from the estimated pricing equation. From equation (7) we can decompose observed prices into four components. The first two terms are standard features of differentiated-product equilibria: $\mathbf{c}$ is the marginal cost (embedding both observed and unobserved effects); and, $\mathbf{\Omega}^{-1}\mathbf{s}$ captures the standard markup in the Bertrand-Nash framework, which depends on both product ownership patterns and the substitution matrix (elasticities). The last two terms on the right-hand side of equation (7) capture the additional effects of royalties—specifically, $diag(\mathbf{x})\mathbf{r}$

[8] The fact that our point estimate is somewhat below the observed technology fee may indicate that our estimates are somewhat conservative. One should keep in mind, however, that the technology fee structure setup by Monsanto was intended to pursue multiple goals, including to get farmers to understand the source of the seed price increase. Seed companies likely shared part of the technology fee revenue with participants in the seed production and distribution system to promote their acceptance of the novelty of GE seeds.

reflects the "marginal cost" effect of royalties, and the final term captures the "strategic effect" of royalties. Given the estimated marginal cost and royalty rates, and the estimated nested-logit demand structure, we can compute the relative importance of each of these components in the final seed price. **Table 6** reports these estimates (these are averages over all product-market combinations in the data).

Table 6. Fractional Decomposition of Observed Seed Prices, 2002–2016

	All products	Products not paying royalties	Royalty paying products
Marginal Cost	64.1%	70.4%	59.2%
Standard Markup	19.7%	22.4%	17.6%
Royalty	16.1%	7.1%	23.2%
cost effect of royalties	12.6%	0.0%	22.5%
strategic effect of royalties	3.5%	7.1%	0.7%
Number of product-market observations	71,091	31,289	39,802

Note: this table reports a decomposition of observed equilibrium prices into separate components, as per equation (7). The reported percent contribution of the separate components are averages over all observations.

Table 6 shows that the licensing of GE traits accounts for a major portion of GE product prices. For licensees, royalty payments are actually slightly higher than the standard markup component on the seed products they sell, and more than one-third of the estimated marginal production costs. The "cost effect" of royalties, perhaps unsurprisingly, is larger than the strategic effect. The latter, however, is not insignificant—over all products not paying royalties (which includes conventional products as well as GE products where the product-selling firm owns the trait), the strategic effect accounts for 7.1% of the final seed price (about one-third of the standard markup component).

7. Counterfactuals

We use the estimated model to conduct counterfactual simulations that provide additional insight into the exercise of market power in the seed industry, and the role of trait licensing and cross-licensing in this setting. We consider three counterfactual scenarios: (*a*) No royalties; (*b*) Full collusion; and, (*c*) No licensing. Scenario (*a*) pertains to the hypothetical scenario where all GE traits are in the public domain (i.e., there is no ownership of the various GE traits but they are freely available to all seed firms) and may be informative as to the overall (ex post) pricing effects of proprietary innovation in the seed industry. Scenario (*b*) helps frame the extent of market power in the baseline, arising from both germplasm and GE trait ownership, relative to what would be possible to a monopolist (without price discrimination). Scenario (*c*) addresses the question of whether the licensing of GE traits in the industry is pro- or anti-competitive, on balance. Such a counterfactual involves complex issues, and thus we carry it out only for the case of GT soybeans.

7.1 Market Power in the US Seed Industry

Table 7 reports results for the foregoing counterfactuals, along with the baseline. [9] We summarize estimated outcomes for three groups of seed companies, in addition to the seed industry aggregate. We single out Monsanto because it was the leader in the development of GE traits and, over the period considered, had by far the largest share of licensed traits (100% of GT soybeans, and 71% of GE maize, in terms of acreage planted). The remaining seed companies are in two groups: major companies (DuPont, Dow AgroSciences, and Syngenta) who, along with Monsanto, are large players in the US seed industry (**Table 1**); and, all other minor companies.

Starting with the baseline results in **Table 7** we note that, in the aggregate, the maize seed market is larger than the soybean seed market. This is true in physical terms (as measured by planted acres), and even more so in revenue terms because maize seeds, on average, command a higher unit price than soybeans (this is because maize seeds are hybrids, so their production is more

[9] For all scenarios, equilibrium prices are computed using the fixed-point algorithm described in Morrow and Skerlos (2011).

costly than that of soybeans, and the hybrid technology permits a stronger exercise of intellectual property on the underlying germplasm). Despite the fact that there is essentially only one soybean GE trait over the 2002–2016 period, the average GE adoption rate is higher for soybeans (92.9%) than for maize (77%). The four largest parent companies (Monsanto and the three included in "other major") have an average market share of about 73%. We calculate total quasi-profits as the difference between total revenues and estimated production costs (using the estimated marginal costs). By construction, they do not include possible fixed costs, and in particular do not include R&D expenditures (which are sizeable in this industry). Thus, such profits are rather large, exceeding $3 billion per year (in constant 2011 dollars). The share of industry profit accruing to the top four companies is about 87%. In addition to reflecting differences in retail prices and marginal production costs, the fact that the large companies' profit share exceeds their seed revenue share is also due to the existence of royalties for GE traits. Table 7 explicitly reports estimated net royalties. By "net" here we mean the difference between royalty revenues and royalty payments, resulting from the cross-licensing structure discussed earlier. Monsanto is the only company with positive net royalties, and in fact for Monsanto, such royalties constitute about 45% of their total quasi-profits.

The case of "no royalties" illustrates a hypothetical scenario where all GE traits remain in the market but are freely available (as would result, for example, if they were publicly provided). To conduct this counterfactual, we re-compute prices, quantities and profits for the special case when there are no GE licensing arrangements ($\mathbf{x} = \mathbf{0}$ and $\mathbf{r} = \mathbf{0}$), which reduces the pricing equation to $\mathbf{p} = \mathbf{c} + \boldsymbol{\Omega}^{-1}\mathbf{s}$. It is apparent from **Table 7**, which provides the changes in each variable relative to the baseline, that freely available GE traits would lead to lower equilibrium seed prices—maize prices decline by about 16% and soybean prices by about 21%. In the aggregate, however, it is maize plantings that respond the most to the general decline in seed prices (because maize seed prices are higher in the baseline and maize seed demand is more elastic than soybean seed demand). Seed companies' quasi-profits fall in the aggregate by about 44%, with Monsanto being the largest loser. Minor seed companies (who must license all of the GE traits in the baseline), however, experience a sizeable increase in their quasi-profits.

For all counterfactuals, we also report the change, relative to the baseline, in surplus for final users (farmers who buy seeds). The welfare metric used is the standard change in consumer surplus, as implied by the estimated demand model, computed by the log-sum formula corresponding to the nested logit model (Björnerstedt and Verboven 2016; Ciliberto, Moschini, and Perry 2019):

$$\Delta CS_m = \frac{1}{\alpha}\left(\hat{I}_m - \tilde{I}_m\right)$$

where $\hat{I}_m$ is the predicted inclusive value in the counterfactual and $\tilde{I}_m$ is the predicted inclusive value in the baseline (see Appendix D for more details). We obtain total dollar values within each market m by multiplying ΔCS_m by the potential market size. For the "no royalties" scenario, unsurprisingly (given the decline in seed prices), we find a major increase in consumer surplus—about $1.8 billion per year (in constant 2001 dollars).

The "full collusion" scenario in **Table 7** reports results from hypothetical monopoly pricing in the US seed industry. The model predicts that full collusion would result in major price increases—about 182% for soybean seeds and 123% for maize seeds. Correspondingly, farmers would reduce planted acres of both crops by a considerable amount (45% for soybeans and 35% for maize). Were they able to fully collude on prices, firms in this industry would essentially double their quasi-profit. The large increase in seed prices in this scenario, relative to the baseline, means that farmers would suffer major negative effects, with a loss of about $9.5 billion per year. Albeit unlikely, the "full collusion" scenario highlights the risks of excessive market power in the seed industry. Seed demand is highly inelastic, which is ultimately a consequence of two structural features: crop acreage plantings (crop supply) is known to be inelastic (e.g., Kim and Moschini 2019); and, there is very limited substitution between land and seeds (in fact, our model assumes fixed proportion between these two inputs). The large profit opportunities for collusion also provide an explanation for the drivers of consolidation in this industry, and a reason for concerns at the antitrust level.

Table 7. Baseline and Counterfactual Outcomes

	Monsanto	Other Major	Other Minor	Industry
BASELINE				
Quantity maize ‡	20.78	31.09	20.33	72.19
Quantity soybeans ‡	16.21	25.27	19.41	60.89
Average price maize §	87.24	72.77	65.36	74.85
Average price soybeans §	50.23	48.64	46.87	48.50
Maize GE adoption	93.4%	75.9%	61.9%	77.0%
Soybean GE adoption	98.2%	94.7%	86.0%	92.9%
Market shares (revenue)	31.4%	41.8%	26.8%	100.0%
Net royalties †	753	−331	−422	0
Firms' quasi-profit †	1,687	989	412	3,087
NO ROYALTIES				
Δ Quantity maize	−1.0%	−2.2%	48.6%	12.5%
Δ Quantity soybeans	−11.0%	0.8%	−0.9%	−2.9%
Δ Average price maize	−14.7%	−16.9%	−13.1%	−16.3%
Δ Average price soybeans	−19.9%	−22.0%	−20.9%	−21.2%
Δ Firms' quasi-profit †	−1,204	−247	115	−1,336
Δ Farmers' surplus †				1,805
FULL COLLUSION				
Δ Quantity maize	−33.5%	−40.5%	−27.9%	−34.9%
Δ Quantity soybeans	−45.4%	−40.3%	−51.0%	−45.1%
Δ Average price maize	112.8%	114.7%	151.6%	123.7%
Δ Average price soybeans	182.5%	180.6%	186.3%	183.0%
Δ Firms quasi-profit †	1,048	2,730	2,348	6,126
Δ Farmers' surplus †				−9,533
NO SOYBEAN GT LICENSING				
Δ Quantity maize	9.8%	9.5%	8.9%	9.4%
Δ Quantity soybeans	72.1%	−47.0%	−43.6%	−14.2%
Δ Average price maize	−0.5%	−0.5%	−0.5%	−0.4%
Δ Average price soybeans	−3.4%	−22.5%	−19.9%	−10.4%
Soybean GE adoption	95.8%	––	––	51.2%
Δ Firms' quasi-profit †	−151	−115	−76	−343
Δ Farmers' surplus †				−417

Note: Entries are annual averages over the period 2002–2016. Units: † = $million/year; ‡ = acres million/year; § = $/acre. All monetary values are in 2011 dollars. The group "Other Major" companies comprise DuPont, Dow Agrosciences, and Syngenta. "Other Minor" include all other companies. For counterfactual scenarios, changes (Δ) are relative to the baseline.

7.2 The Role of Licensing

The last counterfactual in **Table 7** addresses a basic question: what if GE developers had not licensed the GE traits they owned? The underlying economic question of interest relates to whether cross-licensing between competitors has pro-competitive or anti-competitive impacts. Both are clearly possible, as discussed earlier. Broad availability of GE traits increases the competitiveness of products sold by licensees. On the other hand, when licensors out-license their own GE traits, they have a strategic incentive to increase the prices of their own products.

It is apparent, however, that a full characterization of a "no licensing" scenario is difficult in the context of our model. This is particularly so for maize seeds, where some companies jointly developed stacked traits and introduced them gradually over the period of study. The soybean seed market, on the other hand, permits a cleaner characterization. For this crop, there was essentially one GE trait over the period of study—glyphosate tolerance—a trait owned fully by one company, Monsanto. Furthermore, earlier acquisitions provided Monsanto with a solid foothold in the seed industry, such that by 2002—when the earlier phase of shakeups and consolidation following the dawn of the GE era in the seed industry, and major court cases had clarified the intellectual property landscape for GE traits—Monsanto was actually in a position to "go it alone" for GE soybean seeds.

The last counterfactual in **Table 7**, therefore, investigates the impact of "no licensing" for the soybean GT trait. Let q_j^{SoyGT} denote an indicator variable equal to 1 whenever product j is a soybean seed product that contains the GT trait. In this scenario, only seeds firms controlled by Monsanto have access to the soybean GT trait, and all other companies are constrained to sell only conventional soybean seeds. That is, we set $q_j^{SoyGT} = 0$ in the expected profit function for all brands not owned by Monsanto. However, implementation of this scenario involves delicate issues that relate to the demand for counterfactual products (seed stripped of one of their characteristics) as well as, somewhat more subtly, to the composition of the choice set in the counterfactual scenario (Ciliberto, Moschini, and Perry 2019).

To illustrate, consider a market where, in the baseline, Pioneer (a DuPont brand) is selling both a conventional soybean seed product and a GT soybean seed product, whereas Stine (an independent seed company) sells only a GT soybean product. For both companies, removal of the GT trait eliminates this characteristic from their products. Simply dropping such products from the counterfactual, however, would artificially decrease the choice set (because Stine would conceivably still sell conventional soybean seeds instead). Keeping all products of the baseline, but modifying their demand by stripping the GT trait from the Pioneer and Stine seeds product, on the other hand, would artificially inflate the choice set because it would leave Pioneer with two conventional soybean seed products. Our solution to this is to maintain a modified product in the absence of duplicates; and, in the case of duplicates, keep the product which was already conventional in the baseline. In this example, the new choice set would contain a Pioneer conventional soybean seed product and a Stine "synthetic" conventional soybean seed product.

In **Table 7** we report the results of this counterfactual. The results of the "no soybean GT licensing" scenario are quite interesting and show that, overall, licensing of the GT trait led to higher profit for seed companies and larger surplus for farmers. Had Monsanto retained exclusivity of the GT trait, overall adoption of GT soybeans over the period considered would have dropped from about 93% to 51%. Because of the larger prevalence of conventional seeds, no GT licensing would have led to a decline in the average price of soybean seeds by about 10% (with maize seed prices essentially unaffected). Despite these price changes, it is maize plantings that would have increased the most in the counterfactual, because GE corn traits (which continue to be broadly licensed) are ultimately more valuable to users. Absence of soybean GT licensing would have decreased overall industry quasi-profit by $343 million per year (an 11% drop relative to the baseline). Interestingly, Monsanto itself would have experienced a profit loss ($153 million per year) had it chosen to forgo licensing to seed competitors—retaining exclusive access to the GT trait would have been an inferior strategy. Ultimately, this observation substantiates the role of fundamentals in the seed industry: ownership of distinct germplasm confers value to seed companies, over and above the GE traits made possible by the GE revolution.

8. Conclusion

In this paper, we analyze the role of licensing and cross-licensing in the US seed industry. We extend the standard differentiated-product Bertrand pricing model to include per-unit royalties between seed firms. Using detailed data on farmer seed purchases from 1996 to 2016 with publicly available information on GE trait ownership, we estimate a two-level nested-logit model of demand. The estimated elasticities are then used to recover both marginal costs and royalty rates.

We find that royalties comprise almost half of the overall markup on seed products. Most of the royalty effect comes from the increase in costs incurred by licensees. However, the strategic impact of royalties is non-trivial—the additional cooperation induced by licensing results in a 15% higher markup for all products, and a 24% higher markup on non-royalty paying products.

To further identify the impacts of licensing on profits and farmer welfare, we conduct a counterfactual in which, given demand and marginal costs, all GE traits would be freely available, as would have been the case if they had been publicly developed. This counterfactual demonstrates one of the essential tradeoffs involved in granting patents—seed firms are able to extract a larger share of the surplus as compared to end users. Of course, in the absence of granting patents, firms would not have been able to recover the necessary investment costs required for the development of GE traits in the first place.

Our findings imply that the extensive licensing of GE traits has been beneficial to both seed firms and end users (farmers), notwithstanding the fact that the presence of licensing has a moderate strategic impact on pricing. Had Monsanto elected to maintain exclusive access to its soybean GT trait, the loss in licensing revenue would have more than offset the additional profit they would have obtained through their competitive advantage in the GT trait. In addition, farmers, although facing lower soybean prices overall, would have had reduced access to the GT trait through alternative brands, resulting in an overall net welfare loss.

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SUPPLEMENTARY APPENDIX

Innovation, Licensing, and Competition: Evidence from Genetically Engineered Crops

GianCarlo Moschini and Edward Perry

This draft: 18 September 2024

This Online Appendix consists of the following parts:

Appendix A – Data Description

Appendix B – Seed Prices

Appendix C – Seed Production Technology and Marginal Costs

Appendix D – Choice Probabilites and Inclusive Values

References

Appendix A – Data Description

A.1. Kynetec Data

The main data source used in this study consists of a large set of farm-level observations of seed choices by U.S. corn and soybean farmers for the period 1996-2016. In particular, we use the soybean and corn TraitTrak® datasets, two proprietary datasets developed by Kynetec USA, Inc., a market research company that specializes in the collection of agriculture-related survey data. Kynetec constructs the TraitTrak® data from annual surveys of randomly sampled farmers in the United States. The samples are developed to be representative at the crop reporting district (CRD) level. CRDs are multi-county sub-state regions identified by the National Agricultural Statistics Service of the U.S. Department of Agriculture (USDA). **Table A1** reports some descriptive statistics concerning these data. For the period 1996-2016, the data are based on responses from an average of 4,732 farmers per year for maize and 3,560 farmers per year for soybeans.

Table A1. Descriptive summary of GfK data, 1996-2016

	Corn data set	Soybean data set
No. of states represented	40	29
No. of CRDs represented	237	182
No. of farms per year	4,732	3,560
No. of transactions per farm	4.3	2.9
No. of hybrids/varieties sold	3,650	2,118
No. of brands	218	189

Source: Authors' computation from Kynetec data.

To estimate the market level demand model, several steps were taken to convert the raw GfK farm level corn and soybean datasets into the final combined market level dataset. Each of these steps is described in detail below.

A.1.1 Ownership History

The first major step consisted of updating the ownership information throughout the entire 1996-2016 period. The TraitTrak datasets contain an ownership variable but this variable only codes for firm ownership of a particular brand as of 2016. Because there were some major acquisitions during the period we consider, the firm that owned a particular brand in 2016 was not necessarily the firm that owned that same brand in earlier years. For example, Dupont owned Pioneer in 2016, but did not own Pioneer in 1996. The ownership patterns were reconstructed using publicly sourced information, including Farm Journal, newspaper articles, Fernandez-Cornejo (2004) and Howard (2009).

A.1.2 Outliers and Dropped Observations

Having updated the ownership patterns, we then proceeded to remove outliers from the farm-level corn and soybean datasets. Specifically, we dropped observations in which the planting rate – the ratio of seeds planted to planted acres – was in the bottom 1% or the top 99%. We also dropped observations in which the brand variable was coded as "unidentified" or "unspecified". This accounted for approximately 1% of observations in both corn and soybeans. In the corn dataset, we also dropped observations in which the farmer had planted seed to be sold back to seed firms. Finally, we restricted the analysis to the major corn and soybean producing states. We kept states that had *at least* 1% of the overall sample acreage share in each of corn and soybeans. Thus, if a state had 1.5% of the total sample share in corn but just 0.5% in soybeans, it was dropped. This resulted in a sample consisting of the top 13 corn and soybean producing states: IL, IN, IA, KS, KY, MI, MN, MO, NE, ND, OH, SD, and WI. After dropping outliers and marginal states, the combined corn and soybean dataset consisted of 553,226 observations.

A.1.3 Product Definition

From here, we organized and defined the attributes that characterize a seed product. As noted in the manuscript, a product is defined as a unique combination of five types of characteristics: i) the crop (corn or soybeans); ii) the parent company (e.g., Monsanto); iii) the brand (e.g., Asgrow); iv) the presence (or absence) of GE traits, specifically glyphosate tolerance (GT), corn borer (CB) resistance, and rootworm (RW) resistance; and, (v) the owner(s) of the GE traits (the licensors). Some adjustments were made to the characteristics. First, there were a large number of regional brands with very small market share. For regional brands that didn't capture at least 1% of the national market during the 1996-2016 period, we collapsed these brands into a single category called "Regional". Second, there were three other types of seed traits beyond GT, CB, and RW identified in the data: a non-GE trait in corn that confers tolerance to imidazoline herbicides; a non-GE trait in soybeans that confers tolerance to sulfonylurea herbicides; and a GE trait called LibertyLink, which confers tolerance to glufosinate herbicide in both corn and soybeans. Along with traditional conventional varieties, we classified both LibertyLink and the non-GE herbicide tolerant traits as non-GE during estimation. We classified LibertyLink as non-GE because it had relatively low adoption rates and because most farmers did not actually make use of the LibertyLink trait by spraying glufosinate herbicides. The latter can be explained by the fact that the LibertyLink trait primarily served as a marker gene for *Bt* traits.

A.1.4 Aggregation and Market Shares

Given the product definition, we then aggregated acres and expenditures by product and market. A market is defined as a CRD-year combination. Product shares at the market level were obtained by taking the ratio of total product acres to the potential market size (also in acres), where potential market size includes all active and idled cropland, as identified by the Census of Agriculture. Further details on these data, as well as our definition of the potential market are provided below in the section **Cropland.** The potential market was also adjusted to account for the fact that some soybeans were saved, particularly early in the sample. Saved soybean observations did not include any kind of price information (e.g., cleaning and conditioning costs), precluding their inclusion in the analysis. We subtracted saved soybeans from the potential market size, resulting in the finalized potential market size. After computing market shares, in a small number of cases, total planted corn and soybean acres, i.e., total inside good acres, exceeded the potential market size. This is likely the result of sampling error. In markets where this occurred, we dropped this small number of observations. These modifications resulted in a finalized market level dataset of 89,088 product level observations.

A.1.5 Instrumental Variables

The final step consisted of computing the characteristic based instrumental variables. We first computed the total number of competing products by: market; market and brand; market and parent company; market and crop; market, brand, and crop; and market, parent company, and crop. This resulted in 6 instrumental variables. We then computed the same variables for each the three GE traits plus non-GE products: GT, CB, RW, and non-GE. This resulted in an additional 24 instrumental variables.

A.2 GM Approval Database

To construct the ownership patterns associated with the various GE traits, we utilized the GM approval database, maintained by the International Service for the Acquisition of Agri-biotech Applications (ISAAA) (https://www.isaaa.org/gmapprovaldatabase/). This database provides information on the events and developers associated with each commercialized GM trait. Using this information, we constructed a dataset consisting of the set of commercialized traits observed in the Kynetec data, and the associated developers (owners) for each of these traits. We then merged this dataset with the Kynetec data.

A.3 USDA Data

Two other sources of data were required for estimation of the model. The ***crop sector index for prices paid***, which was used to deflate seed costs, was acquired from the USDA-NASS Quick Stats website: https://quickstats.nass.usda.gov. It can be found using the following query:

Survey->Economics->Prices Paid->Crop Sector->Index for Price Paid, 2011

For a measure of the ***potential markets size*** we rely on cropland measure, also obtained from the Quick Stats website. These data can be found using the following query:

Census->Demographics->Farms & Land & Assets->Ag Land->Area

For a detailed discussion concerning the use of cropland measures, see also the Supplementary Appendix to Ciliberto, Moschini, and Perry (2019).

Appendix B – Seed Prices

Table B1. Seed Prices for U.S. Corn and Soybeans ($/acre), 1995-2016

	Soybeans		--Corn Single Traits--			--Corn Stacked Traits--				--Corn--	
Year	Non-GT	GT	GT Only	CB Only	RW Only	GT-CB	GT-RW	CB-RW	GT-CB-RW	Non-GE	GE
1995										23.01	
1996	16.90	20.71		30.47						24.17	30.47
1997	18.37	26.25		33.72						25.72	33.72
1998	18.97	28.23	31.01	36.32		33.65				26.13	36.10
1999	17.28	28.01	30.50	35.54		33.28				27.07	35.00
2000	17.99	27.30	30.84	35.33		29.15				27.57	34.62
2001	17.67	26.19	31.12	36.43		35.08				27.99	35.34
2002	16.73	26.50	31.61	36.31		36.16				28.02	35.29
2003	17.74	26.07	33.60	37.69	44.77	39.06				29.40	36.94
2004	20.30	27.65	32.72	39.74	43.27	39.03	44.39	49.83		30.61	37.85
2005	20.69	32.76	35.53	38.25	42.22	41.02	43.72	46.47	47.32	31.20	38.60
2006	21.21	32.26	38.59	41.74	44.72	44.24	49.96	49.38	55.41	32.98	43.12
2007	22.95	32.68	41.14	42.29	46.17	45.65	47.78	49.05	52.01	33.66	45.65
2008	25.37	36.23	53.11	49.53	60.69	58.00	61.18	61.51	69.01	41.58	61.13
2009	33.87	45.93	62.20	54.89	41.41	67.02	65.25	66.34	85.56	46.85	74.54
2010	34.97	49.40	67.08	62.00	29.94	70.51	67.87	74.31	89.53	50.43	80.30
2011	39.95	49.67	67.46	67.94	39.42	74.37	86.26	63.32	90.85	53.14	82.46
2012	43.98	53.03	76.79	74.15	74.82	83.43	104.66	78.35	100.07	60.57	91.42
2013	44.70	56.39	78.73	95.58	69.67	88.29	101.01	83.83	107.14	65.48	97.56
2014	48.31	58.74	80.61	90.96		93.19	94.18	95.98	112.67	69.34	103.20
2015	51.43	59.24	81.14	68.37	77.80	94.13	106.75	90.95	112.84	68.01	102.49
2016	52.00	58.48	79.71	70.75		94.79	81.29	87.22	110.51	69.40	101.03

Note: This table reports average soybean and corn seed prices in the sample used to estimate the demand model, as per the farm level data described in Appendix A.1. These data are use in Figure 1 in the main text. Source: Authors' computation on Kynetec data.

Appendix C. Seed Production Technology and Marginal Costs

Seed production is a multi-stage process that encompasses a large number of steps and typically spans multiple years. Just like other processes, it has benefited from innovations and the adoption of new technologies. But the basic structure of seed production is constrained by the nature of the biological processes involved, and has remained fairly stable over the last several decades (Le Buanec 2007). A simplified description, that applies to both corn and soybeans, involves essentially three main stages (Lamkey 2004). (*a*) The R&D phase, where breeders develop germplasm with desirable attributes. The output of this phase is so-called "breeder seed," from which all the seed sold to farmers can be traced back to. (*b*) The multiplication of breeder seed to obtain larger quantities of "foundation" or "parent" seed to be used for final seed production. (*c*) The production of hybrid and/or certified seed that can be sold to farmers. These stages require different specialized expertise, and for most seed companies each is carried out by a different department. Throughout, quality control and maintenance of adequate genetic purity is essential.

Stage (*a*) includes the R&D activities. Several steps of the germaplasm development phase are common, regardless of whether the desired end result is a conventional or a GE variety. The latter, of course, requires additional steps: plant tissue transformation, regeneration, and introgression of the transformed plant into the desired germplasm line. Beyond the introduction of foreign genes, the R&D phase has been affected by scientific advances in biology and genomics, and associated technological innovations, such as marker-assisted selection (Godwin et al. 2019). This phase can be a long and uncertain process, not all research trajectories pan out, but successful projects yield plants with stable and uniform genetic makeup and, for transgenic varieties, the desired GE trait. These attributes are encapsulated into so-called "breeder seed," from which all seed eventually sold to farmers is derived.

Starting with small quantities of "breeder seed," the task of stage (*b*) and stage (*c*) are to reproduce and multiply seeds while maintaining the desired purity. The specific characterization of these phases, and of the constituent activities in each, differ somewhat between corn and soybeans (corn is originally an open pollinated grass, although the process is geared toward the production of hybrid seeds, whereas soybean is a closely-pollinated oilseed). For concreteness, let's consider corn (Wych 1988; MacRobert et al. 2014). In stage (*b*), breeder seed is bulked up by repeated planting and harvesting, with the goal of having enough quantities to make the final hybrid cross. Bulking up requires stringent protocols (including such things as isolation distances of fields, and identification and removal of off-types), often subject to regulatory standards. A challenge is to ensure that the genetic purity of the original breeder seed does not decline with these successive generations of seed bulking. Once enough quantities of such "foundation seed" (as the output of bulking up breeder seed is often called) is available, production can move to stage (*c*), where inbred pure lines are crossed to obtain the seed that is sold to farmers. For a standard "single cross" hybrid, foundation seed for two inbred parent lines are needed, one serving as the seed bearing (female) plant and one providing the pollen (male plant). This production stage requires specific and onerous field practices, such as detasseling female plants (i.e., removal of the pollen-producing tassels from the female parent plants), and removing male plants after pollination (so that only seed from the female parent is harvested). Throughout, quality control, including various testing and inspection procedures, are necessary. Traceability and identity preservation is key, to avoid contamination at each of the various stages of bulking up and crossing.

Stages (*b*) and (*c*) of seed production are typically carried out in open fields, and require standard agronomic practices such as irrigation, fertilization, and weed and insect control. To speed up these phases, winter nurseries in tropical regions (or in the Southern hemisphere) may be used. Firms often contract with farmers to carry out some of these field operations, although the specificity of seed production may require specialized equipment (relative to standard crop production). Once the hybrid seed is harvested, several activities are still required, including seed shelling, cleaning, sizing (grading), bagging, and storage. Post-harvest quality tests may also be conducted (e.g., germination). Typically, cleaned seed is also treated with fungicides and pesticides to avoid storage losses to pests.

In conclusion, seed production encompasses many sequential stages. The main differences between conventional and GE varieties are at the R&D phase. From the perspective of seed firms, most of those activities are governed by long-run breeding considerations and entail substantial fixed costs. Starting with breeder seed, however, the various activities in stage (*b*) and stage (*c*) described in the foregoing are required for both conventional and GE seed varieties. This justifies our assumption that the associated costs of the "seed production activities" in these two stages is the same across conventional and GE varieties. Of course, such costs are likely different across crops: stages (*b*) and (*c*) are somewhat simpler for soybeans, a self-pollinating plant that reproduces true to type.

Appendix D. Choice Probabilities and Inclusive Values

Figure D1 illustrates the structure of the two-level nested logit used to model farmers' demand for seed products. The choice probability for seed product $j \in J_{hgm}$ (the market share) is:

$$s_{jm} = \frac{exp(\delta_{jm}/(1-\sigma_1)}{exp(I_{hg}\ \ /(1-\sigma_1)} \frac{exp\left(I_{hgm}/(1-\sigma_2)\right)}{exp\left(I_{gm}/(1-\sigma_2)\right)} \frac{exp(\,I_{gm})}{exp(\,I_m)},$$

where I_{hg} , I_{gm} and I_m are "inclusive values" defined as follows (Björnerstedt and Verboven 2016):

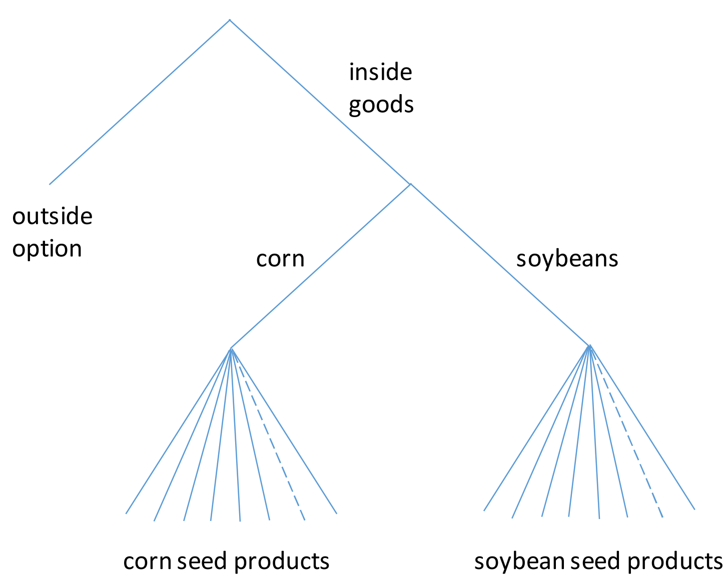
$$I_{hgm} = (1-\sigma_1)\, ln \sum\nolimits_{k \in J_{hgm}} exp\left(\tfrac{\delta_{km}}{(1-\sigma_1)}\right)$$

$$I_{gm} = (1-\sigma_2)\, ln \sum\nolimits_{h \in \{1,2\}} exp\left(\tfrac{I_{hg}}{(1-\sigma_2)}\right)$$

$$I_m = ln\left(1 + exp(\,I_{gm})\right)$$

The inclusive values express the expected utility associated with each nest. I_m is the expected utility associated with all options (both inside and outside) in market m (up to an unidentified constant and scale). As expressed in the main text, the change in expected consumer surplus is then given by: $\Delta CS_m = (1/\alpha)(\hat{I}_m - \tilde{I}_m)$, where $\hat{I}_m$ is the predicted inclusive value in the counterfactual and $\tilde{I}_m$ is the predicted inclusive value in the baseline.

Figure D1. Structure of the two-level nested logit model



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