Valuing Product Innovation: Genetically Engineered Varieties in U.S. Corn and Soybeans

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Abstract

We develop and estimate a discrete-choice model of differentiated products for the corn and soybean seed industry in the United States to assess the welfare impact of genetically engineered (GE) crop varieties. We use a unique dataset, spanning the period 1996-2011, that contains rich information on the adoption of GE traits. Using a two-level nested logit model, we estimate that U.S. farmers are willing to pay a significant premium for GE traits, and this value has increased over time. Over the last five years of the sample, our results imply that farmers' average willingness to pay for glyphosate tolerance in soybeans was $24/acre/year. During the same period, farmers' willingness to pay for a common triple-stack in corn that includes two insect resistance traits and glyphosate tolerance was $35/acre/year. To compute overall welfare estimates, we evaluate counterfactual scenarios in which GE varieties are not available, with counterfactual non-GE seed prices predicted by a hedonic price equation. Counterfactual scenarios are adjusted to account for the fact that GE crop varieties crowded out non-GE varieties by the end of our sample. We estimate that GE innovations increased farmers' welfare by more than $14 billion over the period of study. We also find that the development and diffusion of GE traits increased U.S. corn and soybean seed industry revenues by nearly $23 billion over this period. Thus, seed firms have been able to appropriate the larger share of the *ex post* value of innovation created by GE technologies.

Key Words: Discrete choice, Innovation, Nested logit, Product characteristics, Seed demand, Transgenic crops, Welfare

JEL Codes: L11, L13, O13, Q12.

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1. INTRODUCTION

Innovation, in the form of new and improved crop varieties, has long played a critical role in the quest to ensure sufficient food supply for a rapidly growing world population. Conventional breeding activities have led to remarkable successes, such as hybrid maize (Griliches 1957) and the green revolution (Evenson and Gollin 2003). Genetically engineered (GE) crop varieties build on this tradition by exploiting the recombinant DNA tools of modern biotechnology. First introduced commercially in 1996, by most standards GE varieties have been very successful (Moschini, 2008). Despite being essentially limited to four main crops (maize, soybean, cotton, and canola), as of 2016 GE varieties were grown on more than 457 million acres worldwide. The United States has been at the forefront of these developments: in 2016, GE varieties were planted on more than 180 million acres of U.S. farmland, nearly 95% of which was maize and soybeans (ISAAA 2016).

Notwithstanding their productivity-enhancing potential, GE crops have been highly controversial. Concerns raised include the fear that GE products are harmful to human health and/or the environment, and ethical objections related to human manipulation of the DNA of living plants and animals. Many of these concerns have been allayed (Bennett et al. 2013). In particular, the environmental impacts of GE varieties appear to be generally positive (NRC 2010, Barrows, Sexton, and Zilberman 2014). However, a separate persistent source of public mistrust relates to the ownership interests of multinational corporations that commercialize GE products. Unlike innovations underpinning the green revolution, which were largely the result of publicly-sponsored research and development (R&D) activities (Wright 2012), GE crop varieties have been primarily developed by private firms, with U.S. seed companies (Monsanto *in primis*) at the forefront. The proprietary nature of GE technologies, and an ongoing consolidation of the seed and agrochemical industry, has heightened concerns about the pricing of these new products, their contribution to welfare, and the actual beneficiaries of the innovation (Clancy and Moschini 2017).

In this paper we provide novel econometric evidence on the welfare effects of the introduction of GE crop varieties. We draw on a large, proprietary dataset of plot-level seed choices by a representative sample of U.S. farmers for the two most important GE crops, corn and soybeans. The data span the period from 1996 (the year GE corn and soybean varieties were first introduced) to 2011 (by which time the average adoption rate of GE varieties exceeded 90%), and contain information on the specific seed products that farmers buy—brand, amount bought, area planted, price paid, and which (if any) GE traits are included in the seed. The richness of the data allows us to estimate an explicit structural model of farmers' demand for seed varieties rooted in the theory of discrete choice in a differentiated product setting (Anderson, De Palma and Thisse 1992). Although this model pertains to a production input (seeds) used by competitive firms, rather than consumer products, it is nonetheless in the tradition of the empirical industrial organization (IO) literature on demand estimation in industries with differentiated products (Berry 1994; Goldberg 1995; Berry, Levinsohn and Pakes 1995; Nevo 2001). This demand model provides the structural foundation for evaluating the welfare impacts of the introduction of new characteristics—GE traits—into seed products, along the lines of the seminal contributions of Trajtenberg (1989) and Petrin (2002).

We estimate the welfare gain attributable to GE traits, and its distribution between farmers and seed manufacturers, by simulating counterfactual scenarios of the U.S. corn and soybean seed markets without GE traits as an available technology. Construction of these counterfactual scenarios proceeds in three steps. First, we specify and estimate a discrete choice model of seed demand that presumes individual profit maximizing choices, with farmers modeled as choosing between all corn and soybean varieties (in addition to the outside option). Specifically, we model the demand for corn and soybean seed products using a two-level nested logit specification (Verboven 1996; Bjornerstedt and Verboven 2016). The upper level consists of the outside option (planting a crop other than corn or soybeans, or not planting at all) and the set of inside options, the latter encompassing all corn and soybean seed products. The inside options are partitioned into two subgroups, one for soybean seed products and the other for corn seed products. This two-level nested specification is particularly suited to the institutional realities of the problem we study, including the role played by the widespread practice of crop rotation.

The estimates from the demand model allow us to infer the willingness-to-pay (WTP) of farmers for seed products over time, and, more specifically, for the GE traits progressively embedded into seed varieties. Estimated WTP for GE traits do not convey the net benefit to farmers of the new technology, however. For that purpose, we need to account for the price premia commanded by varieties embedding GE trait combinations, as well as the likely competitive price effect on non-GE varieties. Hence, our second step is to determine the seed prices that would have been charged had GE seeds not been introduced (the "counterfactual prices"). We follow Hausman and Leonard (2002) and take a reduced-form approach that is agnostic as to the actual mode of competition in the seed industry. In so doing we circumvent the problematic issue of how to model a supply side that is characterized by a complex web of GE trait cross-licensing agreements (the terms of which are confidential) between seed firms. In practice, we estimate a hedonic regression that includes a post-

GE indicator variable that is equal to one for any observation in a market for which a GE variety is available (otherwise, this variable is equal to zero).

The final step consists of computing farmers' counterfactual expected profits by using the structure of the estimated seed demand model together with counterfactual prices. We do so for three alternative counterfactual choice sets. One option is simply to remove all seed products with GE traits from farmers' choice sets. This is labeled as the "Naïve" scenario because it ignores the fact that, as GE seeds became widely adopted over time, the set of available non-GE seeds was increasingly reduced. The crowding out of existing products by new products is an issue that has received relatively little explicit attention (an exception is Eizenberg 2014). In our context, the Naïve scenario entails reduced farmers' choice sets, particularly in the latter part of our sample. Insofar as this feature of the counterfactual is artificial, it will bias upward the estimated welfare gain from GE traits. To address this problem, we construct two other counterfactual product choice sets by removing the GE trait characteristics from any GE product available in a market, while presuming that this results in a viable seed product. In all cases, the hedonic price function permits us to impute counterfactual prices for all products in the counterfactual choice sets.

Given the demand model estimates, counterfactual prices, and the counterfactual product choice sets, we compute the change in expected profit for U.S. farmers due to the availability of the GE technology. We also use the estimated model to infer the additional revenues accruing to seed companies from the ability to market products embedding GE traits. This can be interpreted as the *ex post* return to R&D activities that led to the development of GE varieties. In the most conservative counterfactual scenario, we find that the availability of GE varieties increased farmers' welfare by about $14.9 billion overall over the period of study, or by $6.49/year per acre of corn or soybeans grown. In the Naïve scenario (where GE products are entirely removed from the choice set), the welfare estimates are about three times larger at nearly $45 billion, or $19.97/acre/year. Thus, accounting for the fact that GE products crowded out non-GE products has a substantial impact on the estimated welfare gains. The development and diffusion of GE traits is estimated to have increased seed revenue, in the U.S. corn and soybean industry, by about $23 billion over the period of study. Hence, it seems that the seed industry has been able to appropriate the larger share of the *ex post* value created by the GE technology.

Our analysis adds to the literature on the estimation of the value of product innovation (Trajtenberg, 1989; Hausman, 1996; Petrin, 2002; Nevo 2013; Eizenberg, 2014; Allenby et al., 2014) by focusing squarely on the introduction of new characteristics (the GE traits). In particular, both the data and the econometric framework that we use in this paper are new for the purpose of assessing the welfare impacts of GE crop varieties. Earlier studies on this topic (Falck-Zepeda, Traxler, and Nelson, 2000; Moschini, Lapan, and Sobolevsky, 2000) lacked an econometric backbone and instead relied on indirect evidence to parameterize partial equilibrium models that could be used for counterfactual analysis. As such, they were ill suited to capture the impact of seed pricing of GE crops that is critical in this setting. Using a subset of the proprietary data employed in this paper, Shi, Chavas, and Stiegert (2010) (with extensions in Shi, Stiegert, and Chavas 2011, and Shi et al. 2012) estimate hedonic regressions for the period 2000-2007 and find positive premiums for most GE traits in both corn and soybeans, compared with traditional varieties. But, unlike the present paper, these studies do not model farmers' seed demand explicitly and thus lack the necessary structure to infer welfare effects.

The paper is organized as follows. Section 2 provides background on the introduction of GE traits in soybean and corn seeds, their adoption, and the evolution of market shares. Section 3 presents the data used in the econometric analysis. Section 4 develops the discrete-choice farmers' seed demand model. Section 5 reports the estimation results for this model. Section 6 presents the welfare analysis: farmers' WTP estimates, farmers' estimated increase in expected profit due to GE innovations, and the increase in seed industry revenues due to GE traits. Section 7 concludes.

2. BACKGROUND: GE TRAITS IN U.S. CORN AND SOYBEAN SEEDS

The distinguishing feature of GE crops (also known as transgenic crops) is that their genome contains one or more foreign genes that express desirable traits. In corn and soybeans, these traits encompass two sets of attributes: herbicide tolerance (HT) and insect resistance (IR). The vast majority of HT crops are tolerant to glyphosate, a broad spectrum herbicide marketed by Monsanto under the trademark Roundup®. IR crops embed one or more genes from the bacterium *Bacillus thuringiensis* (hence the widely used "*Bt* " moniker), which emit proteins that are toxic to certain insects. For soybeans, the only trait with commercial relevance thus far has been glyphosate tolerance (GT), while for corn, both GT and *Bt* traits have been commercialized. Earlier *Bt* traits targeted the larvae stage of a major pest, the European corn borer, and subsequent *Bt* traits targeted corn rootworms. Initially, GE varieties had a single trait, but over time commercial varieties have come to embed multiple GE traits, or what are often referred to as "stacked" GE trait varieties. **Figure 1** charts the diffusion pattern of GE varieties in U.S. soybeans and corn, where "*Bt* maize" refers to varieties with at least one IR trait (alone or with the GT trait), and "GT maize" refers to varieties with the GT trait (alone or in combination with other traits). Adoption has been rapid: GE corn and soybeans were first introduced in the United States in 1996 and within just 10 years accounted for the majority of planted acres in both crops.

GE crops are the most visible agricultural manifestation of modern biotechnology and its use of recombinant DNA techniques. The company Monsanto played a critical pioneering role in this process,[1] and its commitment to the development of GE crops has had major implications for the seed industry. GE traits are valuable to farmers because they offer novel (cost-reducing and/or yield enhancing) tools for weed and insect control. However, these properties alone are not sufficient to guarantee adoption. GE traits need to be combined with proven germplasm—the genetics accumulated from traditional breeding and selection activities that result in high-yielding and desirable commercial seed varieties. Thus, GE traits and germplasm are truly complementary assets (Graff, Rausser and Small 2003), both of which have become extremely valuable to seed manufacturers due to the increasing importance of intellectual property rights (Moschini 2010). Well before the advent of genetic engineering, the corn seed industry had already thrived through its use of hybridization (which requires farmers to buy first generation seeds for each planting) and trade secrets, which together effectively prevent imitation. By contrast, commercial soybeans are self-pollinating and thus reproduce "true to type," allowing farmers to replant seed from the previous season's harvest without any loss in expected yield. The introduction of patented GE traits, and the ability of seed companies to write (and enforce) restrictive retailing contracts forbidding farmers to save and replant seeds that contain such traits, thus significantly increased the profitability of selling soybean seeds.

The quest to commercialize GE traits led to a wave of acquisitions and mergers that promoted a rapid consolidation in the seed industry.[2] When Monsanto originally developed and patented its GE traits it did not have a presence in the seed industry, and thus lacked direct access to commercial seed varieties. As a result, Monsanto pursued two parallel strategies for the commercialization of its GE traits. First, it embarked on a series of acquisitions that, over time, transformed it into the largest seed company in the world. At the same time, Monsanto pursued a policy of aggressively licensing GE traits to other seed companies, which also sped up the availability of GE traits to farmers.

[1] Charles (2002) provides a fascinating account of the road to the commercial development and marketing of the first GE varieties.

[2] For more information on this process, see Fernandez-Cornejo (2004) and UNCTAD (2006).

Monsanto's critical acquisitions included Asgrow (in 1997), Dekalb (in 1998) and Holden Foundation Seeds (in 1997). The early emphasis on broad "life science" companies also led to Monsanto becoming the agricultural subsidiary of Pharmacia Corporation in 2000, only to be spun out as an independent company in 2002. Similar considerations led DuPont to acquire Pioneer, the dominant seed company at the time in 1999. Syngenta was formed in 2000 as an agrochemical and seed business from the consolidation and restructuring of major life science companies (Novartis and AstraZeneca). Dow AgroSciences, a subsidiary of Dow Chemical formed in 1997, acquired Mycogen in 1998. By the year 2000, when AgReliant (a joint venture of KWS and Limagrain) was also formed, the fundamental structure of the corn and soybean seed industry had been established, although a number of other, smaller acquisitions would be made in subsequent years (especially by Monsanto).

Market shares, reported as 4-year averages for the 2000-2015 period, are displayed in **Table 1**. Data for 2000-2011 are from GfK Kynetec, the source of the proprietary data used in the econometric analysis. Because these data are available to us only up to 2011, for the most recent years the market shares reported in **Table 1** are from the Farm Journal, a trade magazine.[3] These market share data show an industry with two dominant firms (Monsanto and DuPont) who control approximately 60% of the soybean seed market and 70% of the corn seed market. Three other firms (Syngenta, Dow AgroSciences, and AgReliant) have considerably smaller but significant presence, with the industry completed by a panoply of local and regional companies. **Table 1** also shows the almost complete disappearance of the once-common practice of seed saving in soybeans (which accounted for more than 25% of soybean planting prior to the advent of GE varieties).

3. DATA

The data 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 1996-2011. In particular, we use the soybean and corn TraitTrak® datasets, two proprietary datasets developed by GfK Kynetec, a unit of a major market research organization that specializes in the collection of agriculture-related survey data. GfK 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, and, from

[3] The market share data reported by Farm Journal are based on polling industry analysts and executives, and have been published since 2009. In the three years (2009-2011) that the Farm Journal and GfK Kynetec data overlap, the firm level shares are very similar.

1996-2011, contain an annual average of 4,716 farmers for maize and 3,573 farmers for soybeans.[4] Importantly, the period we observe covers the early stages of GE trait adoption up to its almost complete diffusion by 2011.

In the survey, farmers are asked about the types (brand and hybrid/variety identity), amounts, and cost of seed they purchase. The seed varieties sold to farmers are highly differentiated, with each variety reflecting the accumulation of many generations of traditional breeding aimed at producing characteristics that match particular agro-climatic conditions. Examples of these characteristics include relative maturity, stalk strength, plant height, dry-down, and resistance to local pests.

For the purpose of this study, we define a seed "product" as a unique combination of four types of characteristics: i) the crop (corn or soybeans); ii) the parent company (e.g., Monsanto); iii) the brand (e.g., Asgrow); and, iv) the presence (or absence) of GE traits, specifically glyphosate tolerance (GT), corn borer (CB) resistance, and rootworm (RW) resistance.[5]

3.1. Traits

Each of the various GE traits were introduced at different times in our sample. In soybeans, the GT trait was introduced by Monsanto in 1996 as Roundup Ready® soybeans, and in corn the GT trait was first commercialized in 1998. The main attraction of the GT trait is that, by allowing post-emergence applications of glyphosate without causing injury to the crop, it greatly facilitates and reduces the cost of weed control.[6] The first *Bt* trait in maize was introduced in 1996 and conferred

[4] CRDs are multi-county sub-state regions identified by the National Agricultural Statistics Service of the U.S. Department of Agriculture (USDA).

[5] In principle, we could define a product at the individual hybrid/variety level. The number of available varieties in any given year, however, is too large to be of practical use. For example, 5,065 distinct corn varieties and 2,141 distinct soybean varieties were purchased in 2007. By contrast, for that year, our definition results in 394 distinct products, which we submit is small enough to be econometrically tractable, and large enough to still capture the fundamental elements of product differentiation in the seed industry.

[6] The GT trait is not the only herbicide tolerant trait in corn and soybeans. There is also a GE trait that provides tolerance to the herbicide glufosinate. This trait was developed by Bayer and marketed under the tradename LibertyLink (LL). It has been available in some corn varieties since 1996 and in some soybean varieties since 2009. In our econometric analysis, we ignore this trait for two reasons. First, it has been rarely adopted, especially in soybeans, where it only became available in very limited quantities late in our sample. In corn, this trait can be found in more commercialized varieties, but this is mostly because it primarily served as a marker gene for the *Bt* traits (a marker gene is used to determine whether the insertion process was successful). Thus, most growers did not intend to use

resistance to the European corn borer (CB). Later *Bt* traits, which provided resistance to various species of corn rootworms (RW), were introduced in 2003. The attractiveness of *Bt* varieties is that they increase expected yields and reduce yield volatility (Fernandez-Cornejo et al., 2014; Xu et al. 2013), while also reducing the need for insecticides to control pests. Unlike GT traits, which are highly complementary to a specific chemical, *Bt* traits substitute for chemical inputs (Perry et al., 2016).

Figure 1 shows that the adoption of GE varieties, however fast by most standards, was gradual. These rates were dictated by both demand and supply-side factors. On the demand side, learning and heterogeneity played a role, especially early on. On the supply side, both the regulatory apparatus and technological constraints have been important.

The advent of GE crops in agriculture has spurred active new regulatory measures.[7] The biosafety regulatory framework for GE products in the United States envisions distinct roles for the USDA, the Environmental Protection Agency (EPA) and the Food and Drug Administration (FDA), and prescribes a fairly lengthy and onerous process for approval. A key element is that the unit of regulation is a single "transformation event" (McHughen and Smyth 2008), which is the unique occurrence of a successful integration of a transgene (which expresses a GE trait) into a plant's genome. Once an event has successfully passed regulatory hurdles (i.e., it is "deregulated," in the jargon of the U.S. regulatory framework), the transgene needs to be embedded into elite commercial seed varieties. The main breeding strategy to achieve this objective is backcrossing, a process that requires several years (Bradford et al. 2005). We note at this juncture that the fact that it takes so long to commercialize a trait plays an important role in the identification strategy we employ in the econometric analysis.

Table 2 reports detailed GE trait adoption rates. Each column provides the annual adoption rate for a specific GE trait combination (thus, in corn, the sum across columns is the total annual GE adoption rate). Among all GE-crop combinations, the most rapidly adopted were GT soybeans, which

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the LibertyLink trait when they purchased varieties that (incidentally) contained it. Indeed, based on pesticide data used in Perry et al. (2016), we found that only a small fraction of corn producers who purchased seed containing the LL trait actually used any glufosinate herbicide. There are also traditionally-bred varieties that are tolerant to the imidazoline herbicide (for corn) and to sulfonylurea herbicides (for soybeans). As with the LL trait, such varieties have had low adoption rates. Because our focus is on the difference in value between GE and non-GE crops, in our primary econometric analysis we ignore these other herbicide tolerance traits.

[7] In some jurisdictions, such as the European Union, GE crops are not allowed for planting (although harvested oilseed products and grains from GE crops are allowed for import).

even surpassed the rate at which corn hybrids were adopted (Griliches 1957). By 2003, over 90% of land was planted to GT soybeans, and by 2011 it was 96%. The adoption of GT maize was slower but still achieved a 90% rate by 2011. The adoption of IR traits has been steady as well, with the CB traits (alone or in combination) attaining a 72% adoption rate and RW traits (alone or in combination) achieving a 55% adoption rate by 2011. This table also illustrates the gradual penetration of stacked-trait varieties. By 2011, the triple stack GT-CB-RW was adopted on 54% of maize acres. Note also that the RW trait, owing to its relatively late introduction, has had little diffusion as a standalone trait, instead becoming available to farmers primarily in combination with other traits.

Table 3 reports nominal per-acre average seed costs for each GE trait combination. These prices reveal three important stylized facts about the seed markets. The first is that all prices have trended up over time. Both GE and non-GE prices more than doubled from 1996 to 2011. The second is that GE varieties command a substantial premium over non-GE varieties. In soybeans, the premium was around $9/acre, and in corn the premium ranged from about $9/acre for standalone trait varieties to nearly $30/acre for varieties with all three GE traits. The third stylized fact is that over time GE prices increased by more than non-GE prices. In soybeans, the increase in this price difference was small, as the average premium in 2011 was about $9, only about $1 greater than the average premium in 1997. In corn, the price difference between GE and traditional varieties widened significantly over time. The average premium for corn with the GT trait, e.g., was just $4-$5 per acre prior to 2005, but then increased significantly to about $16/acre by 2011. Similar increases occurred for the other corn GE combinations.

3.2. Brands

The marketing of seeds relies heavily on brand labels. Well-known and long-standing brands such as Dekalb and Pioneer identify germplasm that was developed over a long period of time, and thus carry an established reputation among growers. Shares and prices for each of the major brands in our sample are reported in **Table 4**.

Most brands have a presence in both corn and soybeans, albeit at a different intensity. For example, Monsanto has primarily marketed corn under the Dekalb brand and soybeans under the Asgrow brand. By contrast, DuPont uses the Pioneer brand heavily in both corn and soybeans. There is also variation in the number of brands held by the different parent companies. Monsanto and Syngenta utilize multiple brands, whereas DuPont almost exclusively uses Pioneer. Brand-specific average prices demonstrate significant variation, reflecting a number of effects, including the average value of the underlying germplasm, and the extent of inclusion of GE traits. The latter explains the particularly low average price of publicly available soybean seeds, which do not include any GE traits.

3.3. Product Lines

An essential step in our empirical discrete choice framework is the definition of a "product." Our goal is to capture, in a tractable way, the essential seed characteristics that matter to buyers: the nature of the germplasm, which is captured by the seed brand, and the presence of GE traits. Hence, as noted earlier, we define a seed product as a unique combination of the crop (e.g., corn), the parent company (e.g., Monsanto), brand (e.g., Dekalb), and the GT, CB, and RW traits. To illustrate further, all varieties sold under the Dekalb brand in the same market, and with the same set of GE traits (say, GT and CB), are treated as one product.

One of the important features to note about our product definition is that the number and type of varieties that are aggregated within each product change over space and time. For example, from 2003 to 2011, the number of Pioneer corn varieties purchased with the GT trait rose from 9 to 75. It is thus more appropriate to think of a "product" as a "product line", one which is subject to change over time. One implication of this is that, within our econometric framework, the value of a GE product line should be permitted to change over time. As more and more hybrids are offered with a particular GE trait combination, a wider range of grower needs can be matched, raising the average value of that trait combination. Thus, in estimating our econometric model we permit the return to GE varieties to differ over three sub-periods. By doing so, we not only permit the return to GE traits to vary in accordance with the range of seeds that incorporate them, but also in accordance with other exogenous changes in the industry (e.g., glyphosate going off patent in 2000).

3.4. Market Definition

Another important component in our empirical framework is the definition of a market, which determines the set of available products to residing farmers. We define a market as a CRD-year combination. As previously noted, CRDs are multi-county, sub-state regions identified by the National Agricultural Statistical Service. We define market at this level for three reasons. First, a CRD is the lowest level at which the GFK Kynetec survey data are designed to be representative. Second, agro-climatic conditions are relatively homogeneous within a given CRD.[8] Finally, this is the spatial definition of markets that seed firms themselves use to analyze competitive issues.[9] Overall, this definitions results in 3,874 markets (CRD-year combinations) encompassing 294 distinct CRDs.[10]

A delicate issue, in this context, concerns the definition of the potential market size. Ideally, in a given market, this is given by the amount of land that could realistically be planted to corn or soybeans. To identify this area, we use cropland measures from the Census of Agriculture (USDA-NASS 2014). This is the main source of data concerning land use in the United States, and it is available at 5-year intervals (Bigelow and Borchers 2017). The cropland measure we use includes "cropland used for crops" (itself encompassing three components: cropland harvested, crop failure, and cultivated summer fallow) and "idle cropland." Perhaps unsurprisingly, we observe very little variation in cropland acres over time. Hence, within each CRD, we assume that the size of potential total seed demand is constant over our sample period, and specifically define it as the maximum of reported cropland across the four censuses that pertain to years encompassed by our sample period (1997, 2002, 2007, and 2012).

Table 5 provides information on the average number of products in each market. For both corn and soybeans, the number of products increased steadily up until 2007 and then declined thereafter. This patterns reflects the fact that, as the adoption of GE traits increased (recall **Figure 1**), more and more varieties became available to farmers both with and without GE traits. Later in the sample, as farmers' demand for transgenic varieties exceeded that for traditionally bred varieties, some of the latter were discontinued. This pattern is more marked in corn because there are three GE traits (GT, CB, and RW), compared to one in soy (GT). The fact that the number of products changed so significantly over time is a distinctive attribute of the industry. As we discuss in more detail below, this has certain challenging implications for estimating the welfare associated with the introduction of GE crops.

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[8] Most corn and soybean varieties are bred to possess characteristics that match a particular agro-climatic region. For example, the more northern U.S. regions have shorter growing seasons, so seeds bred for those regions have shorter maturity periods.

[9] See, for example, Monsanto (2009).

[10] There are 303 CRDs in the contiguous 48 states, but some are never present in the data because of negligible corn and soybean production. Also, some CRDs that are present are not sampled every year by GfK Kynetec. This happened when the expected number of acres grown were too low to warrant the collection of data. On average, our data encompasses 242 CRDs per year.

4. FARMERS' SEED DEMAND

Each unit of observation in the data is a farmer's choice of a seed product, denoted by *j*, to be planted on plot i of size L_i. We model this decision as a discrete choice with a profit maximization objective. The profit from planting plot i with seed product j can be expressed as $\Pi_{ij} = RY_i - W \cdot Z_i - P_j S_i$, where R is the output price, Y_i is total output produced, S_i is the quantity of seed, Z_i is the vector of all inputs apart from seed and land (e.g., fertilizers, labor, energy, …), W is the corresponding vector of input prices, and P_j is the price of seed product *j*. Note that we are omitting the rental price of land in this representation, so profit represents the return to the quasi-fixed input land.

The production function is written as $Y_i = F_j\left(L_i, S_i, Z_i\right)$. Note that this function, in principle, is specific to the identity of seed product j (this captures the fact that, compared with traditional seed products, GE varieties may use different amounts and types of pesticides and/or a different quantity of labor). We assume that this production function satisfies two basic properties: constant returns to scale (i.e., doubling all inputs doubles total output); and, a fixed proportion of land and seed. That is, we can write the production function as

$$(1) \qquad F_j\left(L_i, S_i, Z_i\right) = f_j\left(Z_i / L_i\right) \times \min\left\{L_i\, , \, S_i / \lambda_j\right\}$$

where the parameter λ_j denotes seed density (amount of seed per unit of land). By construction $f_j\left(Z_i / L_i\right)$ is strictly concave in the vector of input intensities Z_i / L_i. For a given plot of size L_i, and given that at an optimal solution $S_i = \lambda_j L_i$, upon an optimal choice of input intensities Z_i / L_i, the per-acre maximized profit can be represented as $\Pi_{ij} / L_i = \pi_j(R,W) - \lambda_j P_j$, where the per-acre profit function $\pi_j(R,W)$ is dual to the per-acre production function $f_j\left(Z_i / L_i\right)$.

Because of the linear homogeneity property of $\pi_j(R,W)$, the per-acre profit function is homogeneous of degree one in the vector of all prices (R,W,P_j). In the econometric application that follows, we pool seed choices across multiple years, during which prices changed dramatically. To account for this, we exploit the homogeneity property and deflate all prices by an appropriate input price index W_I and write per-acre profit in real terms, $\pi_{ij} \equiv \Pi_{ij} / (L_i W_I)$, to obtain

(2) $\pi_{ij} = \pi_j(r,w) - p_j$

where π_{ij} is the profit per acre on plot i when using seed product j, (r,w) is the vector of deflated prices of output and all other inputs, and $p_j \equiv \lambda_j P_j / W_I$ is the deflated price per acre of seed product j.[11]

4.1. The econometric model

Farmers' choices are observed in the context of given markets, where a market is defined as a CRD-year combination. Building on equation (2), we model farmers as selecting the seed product that provides the highest expected profit per acre on plot *i* in market *m*, that is, they choose product *j* such that

(3) $$\max_j \ \pi_{ijm} \ , \quad j \in \{0,1,...,J_m\}$$

where J_m denotes the number of seed products available in market m, and $j = 0$ denotes the outside option.

We specify per-acre profits in (2) as being composed of an observable and unobservable part. The observable part is assumed to be linear in parameters, and to depend on product characteristics, as well as a number of fixed and random effects. Specifically, the per-acre profit of choosing seed product j on plot i in market m is written as:

(4) $$\begin{aligned}\pi_{ijm} &= \gamma_m \cdot x_j - p_{jm} + \xi_{c[j],t[m]} + \xi_{c[j],l[m]} + \xi_{c[j],b[j]} + \xi_{jm} + \nu_{ijm} \\ &\equiv \delta_{jm} + \nu_{ijm}\end{aligned}$$

where the vector x_j comprises indicator variables that code for the presence of one or more GE traits in seed product j (these variables take value zero for conventional seed products), and p_{jm} is the associated price. For the outside option, we follow standard convention and set $\pi_{i0m} = \nu_{i0m}$. Similar to most empirical discrete choice models, the price p_{jm} enters linearly in equation (4). However, in

[11] Specifically, for W_I we use the crop sector index for prices paid, published by the USDA. This index is normalized to equal 1 in 2011, so that all profit and price data are interpreted in 2011 dollars.

contrast to consumer demand models, where linearity is typically a functional form simplification, in our context it follows directly from the structural assumption of fixed proportions between land and seed, a property of the production technology that applies to this setting.

The terms $\xi_{c[j],t[m]}$, $\xi_{c[j],l[m]}$ and $\xi_{c[j],b[j]}$ are, respectively, crop-time, crop-region, and crop-brand fixed effects. The subscript notation follows Gelman and Hill (2007): $c[j]$ indicates the crop output associated with seed product j (either soybeans or corn), $b[j]$ indicates the brand of seed product j (for example, Dekalb), $t[m]$ denotes the year corresponding to market m, and $l[m]$ denotes the CRD (l stands for location) corresponding to market m. This large set of fixed effects controls for unobservable heterogeneity in yields, output, and input prices across time, regions, brands, and crops. The term ξ_{jm} captures the unobserved product-market specific components that motivate our identification discussion below. Following standard notation, the foregoing terms can collectively be denoted δ_{jm}, which captures the mean profit that is common across all plots within market m.

Finally, ν_{ijm} is the unobserved plot-specific component. An important element of corn and soybean farming captured by this term is the effect of crop rotation. The practice of alternating between corn and soybeans on a given plot is very widespread in U.S. agriculture, as it has been shown to increase profit by increasing yields, reducing fertilizer needs and improving weed control (Bullock 1992). Hence, a given plot planted to corn (soybeans) in year $t-1$ is much more likely to be planted to soybean (corn) in year t. Unfortunately, we cannot observe past crop choices for individual plots. However, knowledge of the critical importance of crop rotation motivates the choice of the nested logit model discussed below.

To make the choice model in (3)-(4) operational, we need distributional assumptions on the plot-specific unobservable ν_{ijm}. We maintain that the demand for corn and soybean seed products is best modeled using a two-level nested logit specification (Verboven 1996; Bjornerstedt and Verboven 2016). We specify the upper level as consisting of the outside option and the set of inside options, where the latter consists of all corn and soybean seed products. We then further partition the inside options into two subgroups, one for soybean seed products and the other for corn seed products. This is illustrated in **Figure 2**. Partitioning the choice problem in this way is consistent with the observation that most of U.S. corn and soybeans are produced in the Midwestern states where they are by far the dominant crops. That is, switching to the outside option, from planting either corn or soybeans, is uncommon.[12] Furthermore, as noted earlier, the practice of crop rotation plays an important role in farmers' choices (Hennessy 2006, Hendricks, Smith and Sumner 2014). The presumption is that, for example, if the expected return to a corn seed product on a given plot is unattractive, a grower will typically be much more likely to consider another corn seed product as an alternative, rather than switch to a soybean seed product instead. As shown by Grigolon and Verboven (2014), when such market segments are an important differentiating dimension, the nested logit model can perform as well as computationally more complex random coefficient models.

To implement this nesting structure, let the choice set in market m be partitioned into two mutually exclusive groups denoted by $g \in \{0,1\}$, where $g = 0$ represents the outside option and $g = 1$ represents inside goods. The latter group is further partitioned into two subgroups denoted by $h \in \{1,2\}$, where $h = 1$ represents corn seed products and $h = 2$ represents soybean seed products. We specify the plot-specific unobserved component as follows:

$$(5) \qquad \nu_{ijm} = \varepsilon_{igm} + (1-\sigma_2)\varepsilon_{ihm} + (1-\sigma_1)\varepsilon_{ijm},$$

where, following standard practice, the terms ε_{igm}, ε_{ihm}, and ε_{ijm} are assumed to possess the unique distribution such that the terms of interest have an extreme value distribution (Berry 1994, Verboven 1996).

The terms σ_1 and σ_2 are the nesting parameters that correspond to the group and subgroup levels, respectively, and measure the correlation between the unobservable components of different products within the same subgroup (σ_1) and within the same group (σ_2). If σ_1 is positive and σ_2 is equal to zero, then farmer preferences are only correlated across seed products in the same subgroup (soybeans or corn), and soybean and corn seed products are not substitutes in the eyes of the farmer. If σ_2 is also positive, then the correlation is also across seeds of different crops. If σ_2 is equal to 1, then farmers do not substitute inside goods with the outside good. In order to be consistent with random-utility maximization, it is necessary that $0 \le \sigma_2 \le \sigma_1 \le 1$, which is a testable implication of the model.

[12] Hendricks, Smith and Sumner's (2014) econometric analysis of supply response in Iowa, Illinois and Indiana show that the extensive margin response (transitions between corn or soybeans to other crops) is extremely small.

In any given market, let the set of seed products in subgroup h of group g be denoted J_{hgm}. Then, the choice probability for seed product $j \in J_{hgm}$ (the market share) is given as follows:

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

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

(7) $$I_{hgm} = (1-\sigma_1)\ln \sum_{k \in J_{hgm}} \exp\left(\delta_{km}/(1-\sigma_1)\right)$$

(8) $$I_{gm} = (1-\sigma_2)\ln \sum_{h \in \{1,2\}} \exp\left(I_{hgm}/(1-\sigma_2)\right)$$

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

Again, in our setting, $g = 1$ denotes the group of all inside goods, and this group comprises two subgroups ($h = 1,2$). Based on this specification, and with some manipulation, we obtain the estimating equation for the two-level nested logit:

(10) $$\ln(s_{jm}/s_{0m}) = \beta_m \cdot x_j - \alpha p_{jm} + \sigma_1 \ln(s_{jm}/S_{h1m}) + \sigma_2 \ln(S_{h1m}/S_{1m}) + \xi_{jm} ,$$

where $S_{h1m} \equiv \sum_{j \in J_{h1m}} s_{jm}$ is the aggregate share of all products in subgroup $h \in \{1,2\}$, and $S_{1m} = S_{11m} + S_{21m}$ is the total share of all inside goods. Hence, s_{jm}/S_{h1m} is the (conditional) share of seed product j within subgroup h (i.e., corn or soybean), and S_{h1m}/S_{1m} is the (conditional) share of subgroup h in group $g = 1$ (the group of all inside goods). Finally, $s_{0m} = 1 - S_{1m}$ is the share of the outside option.

As we discuss further below, these shares are endogenous and therefore require instruments. In addition, the parameter that we estimate on the price variable, $\alpha \equiv 1/\mu$, is the reciprocal of the scale parameter μ associated with the IID extreme value error term. This parameter can be interpreted as a measure of preference heterogeneity in the population (Anderson, De Palma, and Thisse 1992).

4.2. Identification

The key identification issue is the endogeneity of seed prices, which seed manufacturers set taking into account the fact that they are competing in an oligopoly, and factoring in differentiation across products. The solution to this problem, which was first proposed by Bresnahan (1987), and later adopted, among others, by Berry (1994) and Berry, Levinsohn and Pakes (1995), consists of assuming that the location of firms' varieties in the product space is exogenous, and this source of exogenous variation across time and geographical markets can be exploited to identify the parameters of the econometric model.

This assumption seems particularly reasonable in the seed industry because individual firms have shown a clear willingness to introduce traits into their seed lines as soon as they become available. Furthermore, as noted earlier, the introduction of traits into germplasm takes several years and thus it is clearly a decision that is predetermined relative to firms' pricing decisions. Seed companies also invest in traditional breeding activities to improve germplasm, but again they have an incentive to commercialize their best products at any given point in time. The turnover of commercialized varieties is fairly high, with varieties exiting a market sometimes after only two or three years. Overall, this suggests that the introduction of new products is predetermined, and is largely exogenous to pricing decisions.

Following Berry, Levinsohn and Pakes (1995) we use functions of the traits in competing varieties as our instruments. Since GE traits are the main characteristics that vary over seed varieties, this amounts to counting up the unique number of GE seed products. Specifically, we calculate four sets of sums. They are the total number of competing products with a particular trait configuration by: (i) market, (ii) company, (iii) crop, and (iv) company and crop. With seven possible crop-trait configurations, there are twenty-eight total instrumental variables.

5. RESULTS

Table 6 presents the estimation results for four different specifications of the seed demand model, which differ by the number of fixed effects that control for unobserved heterogeneity and by the type of logit model (simple logit vs nested logit). Specifically, columns 1 and 2 contain results for the two-level nested specification discussed in Section 4.2, and columns 3 and 4 contain results for the simple logit specification, which is equivalent to the special case $\sigma_1 = \sigma_2 = 0$. Our primary goal with this table is to establish how these modeling differences, and the use of instrumental variables, affect the estimated coefficients and the implied elasticities.

In all four specifications, the coefficients are estimated precisely and the pricing and nested logit terms have the expected signs and ordering. The specification in column 1 is estimated with the richest set of fixed effects, which include year, CRD, and brand fixed effects, each of which is also interacted with a crop dummy variable. The year fixed effects control for temporal industry-wide changes, such as changes in output (corn and soybeans) prices, or changes in the prices of non-seed production inputs (e.g., fuel). The CRD fixed effects control for unobserved, time-invariant regional specific effects, such as the length of the growing season, soil quality, and weed pressure. The brand fixed effects control for unobserved perceived and real differences in the returns to each of the various brands. For example, in a given region, Pioneer seed may be generally regarded by growers as high-yielding, and because of this its prices will be set higher. As it concerns fixed effects, the difference between column 1 and columns 2-4 is that the fixed effects in the latter are not interacted with a crop dummy variable.

Column 1 of **Table 6** contains the most general specification of this table. The price coefficient is statistically significant and negative, as expected, and the nesting parameters are tightly estimated, with an ordering that is consistent with profit maximization ($0 < \hat{\sigma}_2 < \hat{\sigma}_1 < 1$). Their magnitude indicates strong correlation within nests, suggesting that once producers decide on which crop to plant on a given plot they are very unlikely to switch, both to another crop (corn or soybeans), and even more so to something besides corn or soybeans. This finding supports the rationalization of the two-level nested logit specification provided earlier. The remaining estimates presented in column 1 are for the coefficients associated with the GE trait dummy variables. In all cases the estimates are positive indicating that farmers are willing to pay a positive amount for each trait. These coefficients provide the basis for estimating farmers' willingness to pay (WTP) for the innovation of GE traits, which we consider extensively in section 6.

Column 2 in **Table 6** includes fewer controls by postulating year, CRD, and brand fixed effects that are not crop-specific. Relative to column 1, the results remain mostly unchanged, however, the subgroup nesting parameter, σ_2, increases in size and the price coefficient is significantly smaller. This likely reflects the fact that including crop-specific effects controls for crop-specific unobservable differences in products that are correlated with prices. In moving from column 2 to column 3 we move from the two-level nested logit model to the basic logit model. This reduces flexibility in the substitution pattern between seed products (and also means that the coefficients of the price variable are not directly comparable). Finally, column 4 presents results for the simple logit model without instrumental variables for prices. The price coefficient without instruments is substantially smaller (in absolute value) than in column 3. The fact that the price coefficient increases so significantly when going from column 4 to column 3 indicates that prices are indeed endogenous, a finding that is typical of differentiated product markets (Berry, Levinsohn and Pakes 1995; Trajtenberg, 1989).

5.1 Elasticities

To better convey the implications of the different coefficients, **Table 6** also presents mean own and cross-price elasticities. In the two-level nested logit model of Figure 2, for all $j \neq 0$, own-price elasticities are given by (for notational clarity we omit market subscripts):

$$\text{(11)} \qquad \frac{ds_j}{dp_j}\frac{p_j}{s_j} = -\alpha\left(\frac{1}{1-\sigma_1} - \left(\frac{1}{1-\sigma_1} - \frac{1}{1-\sigma_2}\right)\frac{s_j}{S_{h1}} - \frac{\sigma_2}{1-\sigma_2}\frac{s_j}{S_1} - s_j\right)p_j$$

where s_j/S_{h1} is the conditional share of seed product *j* in subgroup h of the group of inside goods ($g = 1$), and s_j/S_1 is the conditional share of seed product *j* in the entire group of inside goods. Given this, the coefficients of the model in column 1 imply a mean own-price elasticity equal to -7.04, which is quite elastic. The estimated own-price elasticities get progressively smaller (in absolute value) in columns 2-4, as we include fewer controls and less flexibility in the substitution patterns. For the basic logit model in column 4, the implied mean own-price elasticity is just -0.25, an inelastic response which is inconsistent with models of profit-maximizing seed firms that sell differentiated products.

The cross-price elasticities, both within seed products of the same crop, and between seed products of different crops, are given by:

$$\text{(12)} \qquad \frac{ds_k}{dp_j}\frac{p_j}{s_k} = \alpha\left(\left(\frac{1}{1-\sigma_1} - \frac{1}{1-\sigma_2}\right)\frac{s_j}{S_{h1}} - \frac{\sigma_2}{1-\sigma_2}\frac{s_j}{S_1} - s_j\right)p_j, \quad \text{if } j \text{ and } k \text{ are in the same subgroup}$$

$$\text{(13)} \qquad \frac{ds_k}{dp_j}\frac{p_j}{s_k} = \alpha\left(-\frac{\sigma_2}{1-\sigma_2}\frac{s_j}{S_1} - s_j\right)p_j, \quad \text{if } j \text{ and } k \text{ are not in the same subgroup}$$

For the most general model of column 1 in **Table 6**, the mean cross-price elasticities are thus 0.48 within a crop (e.g., from a soybean seed product to another soybean seed product) and 0.05 across crops (e.g., from a soybean seed product to a corn seed product). The difference between these mean elasticities underscores the importance of rotation considerations in farmers' seed choices: growers more readily substitute towards products of the same crop in response to price increases in any given seed product. For the outside good, the cross-price elasticity is simply $\alpha s_j p_j$. The estimated cross-price elasticity for the outside good is very small at just 0.02, or about one-fortieth the magnitude of the mean cross-price elasticity for products of the same crop. This indicates that the aggregate demand for corn and soybean seed products is rather inelastic.

5.2 Subadditivity and Time-Varying GE Trait Effects

Table 7 provides results for two additional specifications that expand on the specification in column 1 in **Table 6**. The first column allows for complementarities (or rivalries) among GE traits as inputs. More specifically, there is an additional indicator variable, *Multiple Traits*, that takes a value of one whenever there is more than one GE trait in a seed product.[13] The negative and significant coefficient in **Table 7** for *Multiple Traits* indicates sub-additivity in the *value* of products with multiple GE traits. That is, on average farmers are willing to pay a bit less for each of multiple GE traits compared to what they would pay for those traits in isolation. This result is related to, but distinct from that of Shi et al. (2010), who find sub-additivity in the pricing of stacked GE trait varieties. Our result, being rooted in a structural demand model, relates specifically to the value farmers place on GE traits.

Column 2 of **Table 7** contains the estimates that we use for the welfare analysis. In contrast to column 1, column 2 permits the return to the various GE traits to differ across three sub-periods. As noted, these three sub-periods correspond to important events that likely affected the return to GE products. Two of these events are the expiration of Monsanto's glyphosate patent in 2000, and the sharp increase in crop output prices in 2007 as part of the most recent major commodity price boom (Baffes and Haniotis 2010). The results in column 2 strongly indicate that the returns to GE varieties were indeed different and increasing over these three sub-periods. Specifically, the coefficient on the Soy GT Trait increased from 0.3576 in 1996-2000 to 0.5289 in 2007-2011, and the coefficient on the Corn GT Trait increased from 0.0385 in 1996-2000 to 0.3583 in 2007-2011. These increases are consistent with the fall in glyphosate prices that followed Monsanto's patent expiration: because glyphosate is a complementary product to GT traits, lower prices should increase the value of these traits to farmers. For the CB and RW traits, there were also significant increases, particularly in the final sub-period. This is consistent with CB and RW products being perceived as having a yield

[13] We also estimated regressions with stacked variables for all of the possible GE trait combinations: GT-CB, GT-RW, CB-GT, and GT-CB-RW. We use a generic stacked variable for its parsimony and because certain stacks are very seldom observed. Nonetheless, the results are largely unchanged in these alternative cases.

advantage: as output prices increase, the gap in expected revenues increases, and thus farmers' WTP. The *Multiple Traits* coefficient also changes over time, becoming more negative in the final subperiod. Finally, the own and cross-price elasticities of demand are similar to previous estimates, albeit a bit smaller in magnitude compare to column 1 of **Table 7** and to column 1 of **Table 6**.

Using the estimated coefficients from column 2 in **Table 7**, we compute mean own and cross price elasticities across time (**Table 8).** On average, the own-price elasticities range from -4.17 in the first sub-period to -5.90 in the final sub-period, a 41% increase (in absolute value). In contrast, the mean cross-price elasticity among products of the same crop fell from 0.39 in 1996-2001 to 0.31 in 2007-2011, while the mean cross-price elasticity among products of different crops remained small (0.05 in 1996-2011 and 0.04 in 2007-2011). The drop in cross-price elasticities is primarily due to a more congested product space because, as shown in **Table 5**, the total number of available products increased over time. As a result, for a given price increase, farmers had a larger number of alternatives to turn to, thus reducing the average cross-price elasticity.

The increase in the own-price elasticities over time reflects, *inter alia*, the dynamics of seed prices. As noted by others (Nevo 2000; Bjornerstedt and Verboven 2016), the fact that price enters linearly in the decision-maker payoff function implies that the absolute value of price elasticities increase in prices. The linearity in price is a standard assumption in the discrete choice literature, typically invoked as a convenient parameterization. As noted earlier, however, in our production context price linearity can be rationalized on the basis of a reasonable condition on the production technology (i.e., fixed proportion between land and seeds). In any event, in our data seed prices increase over time, especially in the latter part of the sample. Part of the explanation is that the share of seed products embedding GE traits, which command a price premium, has increased considerably over time. A second source of rising prices was the sharp increase in crop output prices during the commodity price boom that characterized the last few years of our sample (Baffes and Haniotis 2010, Wright 2011). For the seed industry, such commodity price increases represented both a rightward-shift in farmers' seed demand and a cost shock, both likely contributing to increasing seed prices, especially in light of the noncompetitive nature of the seed industry.

6. WELFARE ANALYSIS

The development and commercialization of GE crops has represented a major technological innovation for agriculture. Unlike much prior technological change that was rooted in publicly sponsored agricultural research (Alston and Pardey 1996, Huffman and Evenson 1993), the proprietary nature of GE traits requires appropriate non-competitive market settings to model their welfare impacts (Lapan and Moschini 2004). Previous studies that attempted to estimate these welfare effects lacked both the data and a suitable econometric framework to evaluate the pricing impacts of the introduction of GE seeds. Instead, these studies relied on indirect evidence to parameterize partial equilibrium models used for counterfactual analysis of the impacts of GE crops (Moschini, Lapan and Sobolevsky 2000, Falck-Zepeda, Traxler and Nelson 2000, Sobolevsky, Moschini and Lapan 2005). The estimated seed demand model presented in the foregoing provides the ideal framework for a novel empirical assessment of such welfare effects.

To estimate the value of GE traits on farmers and on seed firms, we proceed in three steps. First, we compute farmers' WTP for GE traits, which provides an initial indication of the gross value of GE technologies to farmers. Second, we estimate the total welfare (i.e., total *net* value) of GE traits to farmers by simulating a counterfactual in which GE traits are not available for purchase. In order to conduct this simulation, however, we also need to estimate what conventional seed prices would have been in the absence of GE products. To this end, we use a reduced-form hedonic approach in the tradition of Hausman and Leonard (2002), the details of which are discussed below. In the final step, we estimate the additional revenue seed firms obtained from GE products.

6.1. Farmers' Willingness-to-Pay for GE Traits

The WTP for a given GE trait combination is the maximum amount ($/acre) that a farmer would be willing to part with in order to have that particular combination added to a seed product line. To calculate farmers' WTP for GE traits, we use the demand estimates from the most general model (column 2 of **Table 7**). In a typical discrete choice random utility framework (e.g., the logit model), the (marginal) WTP for a particular characteristic is given by the ratio of the estimated coefficient on that characteristic to the estimated coefficient on the price variable (Train 2009). Although our latent return function is cardinal and denominated in dollars per acre (rather than utility), the general procedure remains the same: the WTP for a particular GE trait is the ratio of the coefficient associated with that trait and the estimated price coefficient. As noted earlier, the estimated price coefficient is the reciprocal of the scale parameter of the extreme value distribution (i.e., $\alpha = 1/\mu$). Thus, in dividing by the price coefficient, we are simply removing the scale factor from the trait coefficients. For example, the WTP for the GT trait in soybeans is: β_{SoyGT}/α. For a combination of GE traits, the relevant WTP is recovered by dividing the sum of the associated trait coefficients by the price coefficient. For example, the WTP for the stacked combination GT-CB-RW in corn is $(\beta_{CornGT} + \beta_{CB} + \beta_{RW} + \beta_{Multiple})/\alpha$.

Table 9 contains WTP estimates for each of the GE-trait combinations in each of the various sub-periods. Because all prices in the analysis are deflated by an input price index normalized to equal 1 in 2011, all estimates are in real terms (2011 dollars). All of the estimates appear reasonable and are in line with what might be expected given knowledge of seed prices and the observed adoption patterns by farmers. The WTP for the GT trait in soybeans was \$16.68 per acre in the first sub-period, rose to \$23.35/acre in the 2001-2006 sub-period, and then rose slightly again to \$24.66/acre in the 2007-2011 sub-period. The WTP for the Corn GT trait also increased over time but followed a different pattern. From 1996-2000, the WTP for GT corn was only \$1.79/acre. It then grew to \$4.05/acre from 2001-2006, and then increased substantially to \$16.71 from 2007-2011. A similar pattern occurred for the other corn GE traits (CB and RW). For the standalone and stacked combinations, the increase in value was greatest from the second to the third sub-period. The increase in the value of the triple-stack GT-CB-RW was particularly large, from \$10.60 in second sub-period to \$39.41 in the last sub-period.

A common finding among all trait combinations is that their value increased over time, which is consistent with the temporal increase in the observed shares for GE products. One contributing factor has been falling glyphosate prices. Subsequent to the expiration of Monsanto's main glyphosate patent in 2000, the price of glyphosate fell from \$12.42/lb in 2000 to \$4.74/lb in 2011 (note: a standard application is 0.75 lb/acre). Because glyphosate is used more heavily with GT crops, a lower price for this herbicide reduces the production cost of GT crops relative to non-GT crops, reinforcing farmers' adoption incentive. A second factor is rising output prices in the latter years of our sample. The average price received by farmers for corn, as reported by the USDA, increased from \$2.22/bu in the sub-period 2001-2006 to \$4.35/bu in the final sub-period 2007-2011, while for soybeans the corresponding price change was from \$6.03/bu to \$10.30/bu. Naturally, an increase in the output price increases the value of yield-enhancing inputs. As noted, previous work has shown that IR traits in corn increase yields (Nolan and Santos 2012, Xu et al. 2013), and thus higher output prices increase the relative value of the CB and RW traits. A third factor is learning, which may have played a role earlier on. Although the limited availability and breadth of GE seeds was another factor affecting adoption in the first few years, anecdotally it seems that most producers also had an initial trial run with GE crops before wholly committing to this technology. In other words, our WTP methodology is rooted in producers' perceived value of GE traits, which likely increased as evidence of the efficiency-enhancing properties of GE traits accumulated.

A final factor relates to our chosen approach to product definition. Recall that we define a product as a crop-brand-trait combination, which means that we aggregate over varieties within each combination. Over time, the types and number of these varieties changed within each defined product. As an example, the number of Pioneer corn hybrids offered with the GT trait (across all markets) was 9 in 2003 and 75 in 2011. Thus, the various GE trait coefficients also capture the range of varieties that were offered within a particular product line. The wider the range of seeds offered within a product line, the more diverse the set of needs the line could match. For example, it is likely that the 9 GT hybrids offered by Pioneer in 2003 were not as ideally matched to most farmer's needs as the 75 GT hybrids that the same company offered in 2011, and thus the average 2003 value of the Pioneer GT line across all farmers was correspondingly smaller.

It is also worth noting that these values do not convey the actual additional profit associated with farmers' use of GE traits. For that purpose, one needs to account for the additional cost to farmers of acquiring GE trait combinations. It would be tempting to do so by comparing the WTP estimates in **Table 9** with the GE price premiums implicit in observed seed prices (such as those summarized in **Table 3**). However, this would not account for any competitive price effects that GE varieties may have exerted on non-GE products. A more compelling approach, therefore, relies on estimating what seed prices would have been had the innovation of GE traits not happened.

6.2. Counterfactual Prices

The question of what (conventional) seed prices would have been without the GE technology requires a counterfactual analysis because such prices are not observed. A related issue is that other products might have been introduced absent the opportunity to commercialize GE traits. Moreover, prices are not observed for any of the products that could have been developed but were not. The previous empirical literature has largely avoided dealing with this last issue, and has maintained that no other products would have been introduced in the absence of the one that would artificially be excluded. For example, in his seminal paper on the welfare impact of the introduction of minivans, Petrin (2002) did not allow for auto manufacturers to introduce new products had minivans not been developed.

Perhaps the ideal approach to recover counterfactual prices would be to construct a full structural equilibrium model embedding the main drivers of price changes in the industry. With this approach the literature generally maintains that firms behave as Bertrand oligopolists with differentiated products, and then simulates counterfactual solutions under alternative assumptions (Nevo 2001, Petrin 2002, Goeree 2008). Such a structural model presents challenges in our context. This is because, although seed firms own their own germplasm, most of them have engaged in extensive licensing (and cross-licensing) arrangements for GE traits. Hence, the standard Bertrand-Nash price equilibrium conditions for differentiated products do not seem appropriate for this setting. Furthermore, the terms of the GE trait licensing arrangements between firms are not in the public domain (Moss 2010), which makes it problematic to develop a suitable structural representation of the supply side, and undertaking we are leaving for future research.

To proceed, here we take a reduced-form approach that is more agnostic about the actual mode of competition in the seed industry. Specifically, we closely follow Hausman and Leonard (2002), who provide an approach to computing counterfactual prices that does not rely on a structural equilibrium model. We first estimate the following hedonic price equation:

$$p_{jm} = \phi \cdot x_{jm} + \theta_{c[j]} D_m + \zeta_{c[j],t[m]} + \zeta_{c[j],l[m]} + \zeta_{c[j],b[j]} + \upsilon_{jm} \tag{14}$$

where the variable D_m is a post-GE indicator variable that is equal to one for any observation in a market for which a GE variety is available (otherwise, this variable is equal to zero). There are two coefficients for this variable, which vary by crop (soybeans or corn). The coefficients on the 'post-introduction' variables capture, in a reduced-form way, the overall price effects from the introduction of GE innovations. The price effects are identified from the fact that GE varieties were introduced at different times in different regions (i.e., CRDs). Conditional on CRD-specific fixed effects, the time of introduction can be assumed exogenous because of the time constraints that exist for the development of new germplasm and the introduction of GE traits, as discussed in section 3.1. The hedonic price equation in (14) also includes GE trait dummies x_{jm}. The remaining terms in this equation, $\zeta_{c[j],t[m]}$, $\zeta_{c[j],l[m]}$ and $\zeta_{c[j],b[j]}$ are, respectively, crop-year, crop-CRD, and crop-brand fixed effects, and υ_{jm} is an idiosyncratic shock.

Table 10 presents the estimation results for the hedonic price equation. The first row shows the effect of the introduction of the GE varieties on the prices of *all* soybean seed products. We find that the prices of soybean seeds decreased, on average, by \$1.23 when GE products were present. The second row shows the corresponding impact on corn seed prices, which were lower by \$1.15. These are relatively small competitive price effects, suggesting that any substantial welfare effects primarily stem from an increase in the portfolio of choices that the farmers can make, or because of the difference between the prices charged for GE traits and farmers' willingness to pay for them.

The hedonic results also show that GE traits are associated with significantly higher prices, implying that farmers pay considerable premia for GE innovations, as anticipated by the descriptive statistics reported in **Table 3.** For example, we find that the premium for the Soy GT trait was \$15.41 in the 1996-2000 period; it declined to \$13.83 in 2001-2006, and to \$11.42 in 2007-2011. The corn GT trait, instead, saw the premium increase from \$11.45 in the first subperiod to \$13.22 in the final subperiod. The corn CB and RW traits saw the premium decline over time, but the premium was always greater than \$9 over the sample period. Finally, the *Multiple Trait* stack is associated with a subadditivity effect, with prices being lower when GE traits are stacked (this effect amounted to \$4.52 for the last subperiod, where the triple stack GT-CB-RW was widely adopted). This subadditive effect is consistent with previous findings by Shi, Chavas and Stigert (2010).

In addition to being informative of the price premiums that seed companies were able to charge for transgenic varieties, the estimated hedonic equation permits us to infer the prices that would have materialized had GE traits not been introduced in corn and soybean seed varieties. We do this by turning off the categorical variable that is equal to 1 if there was an innovation, and the variables associated with the various GE traits. More specifically, using the estimation output from **Table 10**, the *predicted* prices in the presence of GE traits are given by:

$$\hat{p}_{jm} = \hat{\phi} \cdot x_{jm} + \hat{\theta}_{c[j]} D_m + \hat{\zeta}_{c[j],t[m]} + \hat{\zeta}_{c[j],l[m]} + \hat{\zeta}_{c[j],b[j]} \tag{15}$$

Had transgenic varieties not been introduced, counterfactual predicted prices without GE traits are given by:

$$\tilde{p}_{jm} = \hat{\zeta}_{c[j],t[m]} + \hat{\zeta}_{c[j],l[m]} + \hat{\zeta}_{c[j],b[j]} . \tag{16}$$

In combination with the estimated farmers' WTP for GE traits, the counterfactual prices thus constructed provide the basis for assessing the impact of GE product innovations on farmers.

6.3. GE Seeds and Farmers' Welfare

Computation of the welfare change attributable to the introduction of GE varieties relies on the change in the overall inclusive values, scaled by the price parameter (i.e., the coefficient α). Specifically, in each market m, the change in per acre surplus due to GE traits is given by:

$$\Omega_m \equiv \frac{\left(\hat{I}_m - \tilde{I}_m\right)}{\alpha} \tag{17}$$

where $\hat{I}_m$ is the predicted inclusive value with GE traits and $\tilde{I}_m$ is the predicted inclusive value in a world without GE traits (see equation (9) for the definition of I_m). To obtain the total dollar value of GE traits in market *m*, we multiply Ω_m by the potential market size (in acres) of market *m*, and to compute the dollar value of GE traits in the entire sample, we simply add up the dollar values across all markets.

The primary inputs for equation (17) are the estimated demand parameters ($\alpha, \sigma_1, \sigma_2$) and mean profits δ_{jm}. Using the predicted hedonic prices with and without GE traits, and the estimated terms from the seed demand equations of section 5, predicted mean profits with GE traits are given by:

(18) $$\hat{\delta}_{jm} = \hat{\gamma} \cdot x_{jm} - \hat{p}_{jm} + \hat{\xi}_{c[j],t[m]} + \hat{\xi}_{c[j],l[m]} + \hat{\xi}_{c[j],b[j]} + \hat{\xi}_{jm}.$$

while predicted mean profits without GE traits are given by:

(19) $$\tilde{\delta}_{jm} = -\tilde{p}_{jm} + \hat{\xi}_{c[j],t[m]} + \hat{\xi}_{c[j],l[m]} + \hat{\xi}_{c[j],b[j]} + \hat{\xi}_{jm}.$$

A feature to note about this procedure is that it involves the modification of *characteristics* associated with GE varieties. As previously noted, by the end of the sample GE varieties had not only significantly added to the set of available products, but had also replaced most conventional offerings.[14] In 1996, for example, non-GE varieties comprised 57 out of 66 products; by 2011, they comprised just 38 out of 161 products. If we were to remove GE products entirely from the choice set in 2011 that would leave just 38 products available to growers, a number which likely underestimates what would have been available in the counterfactual. Maintaining such an artificial reduction in non-GE products in the relevant counterfactual has the potential to introduce bias in the estimated welfare gains from GE traits. This is especially problematic in the context of logit models. As noted by Petrin (2002) and Ackerberg and Rysman (2005), among others, the postulated underlying structure implies that an additional option mechanically increases (expected) welfare because it provides another draw from the distribution of random shocks.[15]

[14] The crowding out of old products due to the introduction of new ones is the main concern of Eizenberg's (2014) study of the impact of innovation in central processing units for US personal computers.

[15] Nevo (2011) provides an extended discussion of this point and notes that the logit model *per se* is actually not the source of biased welfare estimates. Rather, the bias arises from using the logit model to predict counterfactual shares.

We address this issue by reporting results for three different counterfactual scenarios. The first one is to simply remove all the GE products from the choice set of the counterfactual scenario, adjust the prices of the remaining conventional products (as per the hedonic price regression), and compute the welfare change of seed users accordingly.[16] As implied by the foregoing discussion, this approach (labeled the "Naïve" scenario) is expected to inflate the estimated welfare effects.

Alternatively, instead of simply removing GE products from the choice set, we modify the characteristics of GE products by removing the GE trait, adjusting the price, and then maintain this "synthetic" product in the counterfactual choice set if it does not duplicate an equivalent non-GE product already present (see below). The presumption is that seed manufacturers would have used the germplasm currently combined with GE traits to commercialize alternative conventional seed products instead. For example, suppose that in a given market there are three seed products: Dekalb-GE-corn, Asgrow-conventional-soybeans, and Pioneer-conventional-corn. If we followed the Naïve approach, removal of GE traits would drop one product from the choice set (the remaining two would be Asgrow-conventional-soybeans and Pioneer-conventional-corn). Instead, with the proposed alternative counterfactual we retain three products: the two pre-existing conventional seed products plus the synthetic Dekalb-non-GE-corn.

Implementation of this alternative procedure to construct the choice set of the counterfactual requires the resolution of a possible ambiguity. In some markets, after modifying the characteristics of GE products, we can end up with "duplicates" vis-à-vis the definition of products used in this study, the only difference being in the unobservable component $\hat{\xi}_{jm}$.[17] This presents the question of which duplicate product to keep in the counterfactual choice set. To proceed, we consider two versions of this alternative approach. In one case, we keep the duplicate with the largest $\hat{\xi}_{jm}$ (i.e., the largest mean expected profit for farmers). We call this the "Keep Best" scenario. In the other case, we keep the duplicate that was originally a non-GE variety, a situation that we label the "Keep Conventional" scenario. We note at this juncture that, by reducing the counterfactual choice set the most, the Naïve scenario will provide the highest penalty for removing GE products, and thus will provide an upper bound for the estimated welfare impact on farmers. Similarly, by picking the seed

[16] In equation (17), this amounts to an $\tilde{I}_m$ in which the exponential terms for GE products have simply been deleted.

[17] For example, in a market where we have both conventional Asgrow soybeans and GT Asgrow soybeans, shutting down the GT traits yields two versions of Asgrow conventional soybean seeds.

product with the largest $\hat{\xi}_{jm}$, the "Keep Best" scenario provides a lower bound for the estimated impact of GE traits on farmers' expected profit.

In addition to overall farmer gains, we also compute the change in expected maximum profit *conditional* on choosing the inside option, as well as conditional on each sub-group (e.g., corn). For example, we compute the welfare gain from GE traits conditional on choosing the inside good. In contrast to equation (17), this is given by $(\hat{I}_{1m} - \tilde{I}_{1m})/\alpha$, where I_{1m} is defined in equation (8). These values are of particular interest because most of the gains associated with GE crops accrue to individuals that actually plant corn or soybeans. Indeed, if there were no changes to the prices of conventional products in the counterfactual, and the set of available conventional products remained fixed, *all* farmer gains from GE traits would accrue to those who actually purchased GE products. Thus, the estimates reported for Ω_{1m}, which are in per-acre terms, will be considerably larger than the estimates for Ω_m because the latter includes plots for which there were no welfare gains from GE crops.

Table 11 reports the estimated farmer welfare gains for each of the three scenarios and across the three sub-periods. The first set of results in **Table 11** pertains to the entire period 1996-2011. We find that, under the "Keep Best" scenario, total farmers' welfare gain from GE innovations is estimated at about $14.7 billion. This table also reports welfare gains on a per acre basis, and we find that on average the farmers' welfare gain, per acre of total cropland, was $2.67 per year. Owing to the extremely low substitution between inside goods and the outside option, discussed earlier, a more interesting figure is farmers' welfare gain per acre of inside good (corn or soybeans). We find that this impact is estimated at $6.49 per acre per year. As discussed, this scenario provides a lower bound for farmers' welfare gains. For the "Keep Conventional" scenario, the estimated farmers' welfare gains are larger. The estimated gains per acre of inside goods are $9.98 per year, a figure that rises to $19.97 per year for the "Naïve" scenario (as noted, an upper bound for farmers' welfare gains).

The remainder of **Table 11** investigates how the estimated welfare gains changed over time. In addition to the results for the entire 1996-2011 period, in this table we also report results for the 1996-2000, 2001-2006, and 2007-2011 subperiods. We see clearly that the estimated welfare gains increased over time. When expressed in terms of inside products, for the "Keep Best" scenario the welfare gains increase from $1.81 per acre per year in 1996-2000 to $11.24 per acre per year in 2007-2011. This trend is common to the other scenarios as well, with the estimated welfare gains rising to

$14.76 per acre of inside goods per year for the "Keep Conventional" scenario, and to $33.10 per acre per year for the "Naïve" scenario, in the 2007-2011 period.

6.4. GE Traits and Seed Industry Revenue

Farmers' willingness to pay a premium for GE traits is equivalent to an upward shift in the demand facing seed companies. Hence, the ability to bundle GE traits with traditional germplasm holds the potential for seed companies to increase prices and boost revenue. In our modeling, we maintain that the hedonic price function estimated in section 6.2 is capturing, in a reduced-form way, equilibrium prices in the corn and soybean seed market. Hence, we can use the estimated counterfactual prices to infer the increase in revenues, due to the ability to commercialize GE traits, that accrued to the seed industry. To compute the benchmark seed revenues we compute the market shares, and associated value of all seed sold, by using the fitted prices of equation (15) along with the estimated seed demand model. For the counterfactual scenario of no GE traits, we compute market shares by using the counterfactual prices of equation (16) along with the estimated demand model. For the latter, similar to the computation of farmers' welfare, we need to take a stand on the choice set that farmers would have faced had GE innovations not occurred. Hence, we again report three possible scenarios, the "keep best," "keep conventional," and "Naïve" approaches.

Table 12 reports the estimated additional revenues for seed manufacturers. Focusing on the "keep best" scenario, we find that over the entire 1996-2011 period, seed firms' sales were greater by nearly $23 billion, with $14.1 billion coming from soybeans and $8.9 billion from corn. Moreover, the additional revenue from GE traits increased over time, reflecting the increased adoption of GE seed varieties and, possibly, changing equilibrium pricing conditions (which, again, we are not modeling in a structural way). Over the last five years of our sample (2007-2011) we find that GE traits boosted seed industry revenue by a total of $13.9 billion, or approximately $2.8 billion per year, and corn contributed significantly more than soybeans to increasing seed industry revenues. This likely reflects the increase in farmers' WTP for corn GE traits (possibly associated with the commodity price boom noted earlier), as well as the increased diffusion of Bt traits in corn varieties (recall **Table 2**).

The estimated seed industry revenue increases reported in **Table 12** are commensurable with the estimated increases in farmers' expected profits reported in **Table 11**. Both measures can be interpreted as the *ex post* welfare gain from GE crops. The interpretation is somewhat different, though. For farmers, the figures in Table 11 can be interpreted as net welfare gains: these are the dollar value of how much better off farmers have been by their ability to purchase GE varieties—

notwithstanding the fact that they had to pay a premium for GE seeds. For the seed industry, on the other hand, increased revenues can be interpreted as *ex post* returns to past investments in R&D activities.[18] Still, comparing the magnitude of gains accruing to farmers and the seed industry we see that the latter has been fairly effective at capturing the value created by GE trait innovations. For example, over the last five years of the sample (2007-2011), for the "keep best" scenarios, farmers' net welfare increased by $8.7 billion whereas the seed industry revenue increased by $13.9 billion. Thus, the seed industry appears to have been able to capture approximately three fifths of the overall monetary value of GE traits.

7. Conclusion

In this paper, we assess the welfare implications of the diffusion of GE traits in U.S. corn and soybeans. We develop a two-level nested logit model of seed demand in which farmers choose the most profitable option among corn and soybean seed varieties (and an outside option). The nesting structure is specified such that at the upper level a farmer chooses whether to plant an inside option (corn or soybeans) or the outside option, and at the lower level she chooses whether to plant corn or soybeans. Conditional on this choice, the farmer chooses a particular seed product. Specifying the demand model in this way not only captures the important mechanism of corn-soybean rotations, but it also partially addresses one of the limitations, noted by Petrin (2002), of using the basic logit model to estimate the welfare impact of new products.

The model is estimated using a unique, large dataset on U.S. corn and soybean seed purchases during the 1996-2011 timeframe. Using the demand estimates, we find that farmers are willing to pay a significant premium for GE traits, and the extent of this willingness has increased significantly over time. We estimate the total net value of GE traits to farmers using counterfactual prices obtained from a reduced-form hedonic approach. Our counterfactual scenarios are adjusted to account for the fact GE crop varieties, over time, crowded out conventional varieties. More specifically, rather than simply removing a GE product from farmers' choice sets, we also simulate scenarios in which modified GE

[18] The implicit assumption, here, is that the marginal production cost to seed firms for GE and non-GE varieties is the same. To put our estimates in context it may be helpful to consider the extent of R&D in this industry. For the five-year period 2007-2011, data reported by Phillips (2014) suggest that the R&D expenditure of the six largest agro-chemical firms, for the seed and GE trait segment, amounted to approximately $13 billion. As for individual companies, publicly available data for Monsanto are most informative because this company's R&D is almost exclusively devoted to seeds and traits. Monsanto's annual disclosures to the U.S. Security and Exchange Commission indicate a total of $5.45 billion in R&D expenditures for the 2007-2011 period.

products are retained in farmers' counterfactual choice sets. In so doing, we avoid the bias that would result from conflating the removal of the GE technology with an artificial reduction in product diversity.

Overall, our results suggest that both U.S. farmers and seed firms have enjoyed significant increases in surplus as a result of GE traits. In the most recent five-year sub-period of our analysis, 2007-2011, our most conservative counterfactual scenario predicts that GE crops were responsible for about $8.7 billion of additional surplus for farmers and about $13.9 billion of additional revenue for seed firms. To the extent that the marginal production cost of GE varieties is approximately the same as the marginal production cost of non-GE varieties, this suggests that seed firms acquired approximately three fifths of the *ex post* surplus imputed to GE traits. We also note that the majority of farmer surplus, particularly prior to 2007, came from GT soybean (rather than GE corn) varieties.

Our work has some important implications for the ongoing debate surrounding GE crops. First, our estimates suggest that, at least up to 2011, farmers still obtained significant net benefits from adopting GE crop varieties, notwithstanding the higher seed prices they paid. It is also notable that seed firms were able to extract the larger share of the *ex post* welfare effects of GE traits. Appropriability of *ex post* returns from innovation is essential to ensure that firms have continuing incentives to invest in R&D. This is particularly important in the modern seed industry, where private R&D funds have vastly exceeded public R&D investments in recent years (Clancy, Fuglie and Heisey 2016). Methodologically, our approach to estimating welfare may be applied to settings in which new products tends to crowd out and replace existing products.

Some caveats are also worth noting in closing. Our analysis of the welfare effects of GE crops pertains to their direct economic consequences for farmers and the seed industry. Welfare implications arising from possible external effects, such as unintended environmental effects, are obviously not encompassed by our methodology. Also, our framework does not capture the possible impact of GE trait adoption on crop output prices, which precludes a fuller welfare impact assessment. Finally, a structural representation of the supply side might be preferable to the reduced-form approach used in this paper. This, however, would require a model that accommodates the complex web of GE trait cross-licensing agreements between seed firms, an undertaking that we leave for future studies.

REFERENCES

Ackerberg, D.A. and Rysman, M., (2005). "Unobserved Product Differentiation in Discrete-Choice Models: Estimating Price Elasticities and Welfare Effects." *RAND Journal of Economics*, pp.771-788.

Allenby, G. M., Brazell, J. D., Howell, J. R., & Rossi, P. E. (2014). "Economic valuation of product features." *Quantitative Marketing and Economics*, *12*(4), 421-456.

Alston, J. M., and Pardey, P. G. (1996). *Making science pay: the economics of agricultural R&D policy*. AEI Press, Washington, D.C.

Anderson, S. P., De Palma, A., & Thisse, J. F. (1992). *Discrete choice theory of product differentiation*. MIT Press.

Baffes, J., and T. Haniotis. *Placing the 2006/08 Commodity Price Boom into Perspective*. World Bank Research Working Paper No. 5371. Washington, D.C., 2010.

Barrows, G., Sexton, S., & Zilberman, D. (2014). "Agricultural Biotechnology: The Promise and Prospects of Genetically Modified Crops." *Journal of Economic Perspectives*, *28*(1), 99-119.

Bennett, A. B., Chi-Ham, C., Barrows, G., Sexton, S., and Zilberman, D. (2013). "Agricultural Biotechnology: Economics, Environment, Ethics, and the Future." *Annual Review of Environment and Resources* 38: 249–279.

Berry, S. T. (1994). "Estimating discrete-choice models of product differentiation." *RAND Journal of Economics*, 25(2): 242-262.

Berry, S., Levinsohn, J., & Pakes, A. (1995). "Automobile prices in market equilibrium." *Econometrica,* 63(4): 841-890.

Bigelow, D.P., and A. Borchers (2017). *Major Uses of Land in the United States*, 2012, EIB-178, U.S. Department of Agriculture, Economic Research Service, August.

Björnerstedt, J., & Verboven, F (2016). "Does Merger Simulation Work? Evidence from the Swedish Analgesics Market." *American Economic Journal: Applied Economics*, 8(3): 125-164.

Bullock, D.G. (1992) "Crop rotation." *Critical reviews in plant sciences* 11(4):309-26.

Bradford, K.J., Van Deynze, A., Gutterson, N., Parrott, W. and Strauss, S.H., 2005. "Regulating transgenic crops sensibly: lessons from plant breeding, biotechnology and genomics." *Nature biotechnology*, *23*(4), pp.439-444.

Bresnahan, T. F. (1987). "Competition and collusion in the American automobile industry: The 1955 price war." *Journal of Industrial Economics* 35(4): 457-482.

Charles, D. (2002). *Lords of the Harvest: Biotech, Big Money, and the Future of Food*. Cambridge, MA: Perseus Publishing.

Clancy, M., K. Fuglie and P. Heisey, (2016). "U.S. Agricultural R&D in an Era of Falling Public Funding." *Amber Waves*, November 10.

Clancy, M.S. and G, Moschini, 2017. "Intellectual Property Rights and the Ascent of Proprietary Innovation in Agriculture," *Annual Review of Resource Economics*, vol. 9, 53-74.

Eizenberg, A. (2014). "Upstream Innovation and Product Variety in the U.S. Home PC Market." *Review of Economic Studies*, 81(3), 1003-1045.

Evenson, Robert E., and Douglas Gollin. 2003. "Assessing the impact of the Green Revolution, 1960 to 2000." *Science* 300, no. 5620, 758-762.

Falck-Zepeda, J. B., Traxler, G. and Nelson, R. G. (2000). "Surplus Distribution from the Introduction of a Biotechnology Innovation." *American Journal of Agricultural Economics* 82: 360–69.

Fernandez-Cornejo, J. (2004). *The Seed Industry in U.S. Agriculture: An Exploration of Data and Information on Crop Seed Markets, Regulation, Industry Structure, and Research and Development*. Washington DC: USDA, AIB No. 786.

Fernandez-Cornejo, J., Wechsler, S. J., Livingston, M., and Mitchell, L. (2014). *Genetically Engineered Crops in the United States*. Economic Research Report Number 162, U.S. Department of Agriculture, February 2014. 34.

Gelman, A. and J. Hill. 2007. *Data analysis using regression and multilevel/hierarchical models*. Cambridge, UK: Cambridge University Press.

Goeree, M. S. (2008). "Limited information and advertising in the US personal computer industry." *Econometrica*, *76*(5), 1017-1074.

Goldberg P.K. 1995. "Product differentiation and oligopoly in international markets: The case of the US automobile industry." *Econometrica* 63(4): 891-951.

Graff GD, Rausser GC, Small AA. 2003. "Agricultural biotechnology's complementary intellectual assets." *Review of Economics and Statistics* 85(2): 349-63.

Grigolon, L., and Verboven, F. (2014). "Nested logit or random coefficients logit? A comparison of alternative discrete choice models of product differentiation." *Review of Economics and Statistics*, 96(5), 916-935.

Griliches, Z. (1957). "Hybrid corn: An exploration in the economics of technological change." *Econometrica*, 501-522.

Hausman, J. A. (1996). "Valuation of new goods under perfect and imperfect competition." In Bresnahan , T.F. and R.J. Gordon, eds., *The economics of new goods* (pp. 207-248). University of Chicago Press.

Hausman, J. A., & Leonard, G. K. (2002). "The competitive effects of a new product introduction: A case study." *The Journal of Industrial Economics*, *50*(3), 237-263.

Hendricks, N.P., A. Smith, and D.A. Sumner. 2014. "Crop Supply Dynamics and the Illusion of Partial Adjustment." *American Journal of Agricultural Economics*, 96(5): 1469-1491.

Hennessy, D.A. 2006. "On monoculture and the structure of crop rotations." *American Journal of Agricultural Economics* 88(4): 900-914.

Huffman, W.E. and Evenson, R.E. (1993). *Science for agriculture: A long-term perspective*. Iowa State University Press, Ames, IA.

ISAAA. 2016. *Global Status of Commercialized Biotech/GM Crops: 2016*. ISAAA Brief No. 52. International Service for the Acquisition of Agri-biotech Applications, Ithaca, NY.

Lapan, H.E., and G. Moschini, 2004. "Innovation and Trade with Endogenous Market Failure: The Case of Genetically Modified Products," *American Journal of Agricultural Economics*, 86: 634-648.

McHughen, Alan, and Stuart Smyth. 2008. "US regulatory system for genetically modified [genetically modified organism (GMO), rDNA or transgenic] crop cultivars." *Plant biotechnology journal,* 6(1): 2-12.

Monsanto (2009). "Observations on Competition in the U.S. Seed Industry", submitted in December 2009 to the Department of Justice. www.monsanto.com/newsviews/pages/monsanto-submission-doj.aspx.

Moschini, G., (2008). "Biotechnology and the Development of Food Markets: Retrospect and Prospects." *European Review of Agricultural Economics* 35(2008): 331–355.

Moschini, G. (2010). "Competition issues in the seed industry and the role of intellectual property." *Choices*, *25*(2), 1-12.

Moschini, G., Lapan, H. and Sobolevsky, A. (2000). "Roundup Ready Soybeans and Welfare Effects in the Soybean Complex." *Agribusiness* 16: 33–55.

Moss, D. L. (2010). Transgenic seed platforms: competition between a rock and a hard place? Addendum. *American Antitrust Institute (AAI) http://www. antitrustinstitute. org/Archives/seed. ashx*.

Nolan E, Santos P. 2012. The contribution of genetic modification to changes in corn yield in the United States. *Amer. J. Agric. Econ*. 94(5): 1171-88

National Research Council (NRC). 2010. *The Impact of Genetically Engineered Crops on Farm Sustainability in the United States*. Washington, D.C.: National Academies Press.

Nevo, A. (2001). Measuring market power in the ready-to-eat cereal industry. *Econometrica*, *69*(2), 307-342.

Nevo, A. (2003). New products, quality changes, and welfare measures computed from estimated demand systems. *Review of Economics and Statistics*, 85(2), 266-275.

Nevo, A. (2011). Empirical models of consumer behavior. *Annual Review of Economics*, 3(1), 51-75.

Perry, E. D., Moschini, G., & Hennessy, D. A. (2016). Testing for complementarity: Glyphosate tolerant soybeans and conservation tillage. *American Journal of Agricultural Economics*, *98*(3), 765-784.

Perry, E.D., F. Ciliberto, D. A. Hennessy, and G. Moschini, 2016. "Genetically engineered crops and pesticide use in U.S. maize and soybeans." *Science Advances* 2, e1600850 (August 31).

Petrin, A. K. (2002). "Quantifying the Benefits of New Products: The Case of the Minivan." *Journal of Political Economy*, *110*(4), 705-729.

Phillips, M. 2014. "Directions in Global Research and Development for Crop Protection Products." Phillips McDougall presentation at *APVMA Future Forum*, Canberra, Australia, 5 November 2014. https://apvma.gov.au/sites/default/files/docs/matthew_phillips_presentation_web_version.pdf

Shi, G., Chavas, J.P., Stiegert, K., (2010). "An analysis of the pricing of traits in the U.S. corn seed market." *American Journal of Agricultural Economics*, 92(5): 1324--1338.

Shi, G., Stiegert, K., Chavas, J.P., (2011). "An analysis of bundle pricing in horizontal and vertical markets: The case of the U.S. cottonseed market." *Agricultural Economics*. 42, supplement: 77-88.

Shi, G., Chavas, J.P., Stiegert, K., (2012). "An analysis of bundle pricing: the case of biotech seeds." *Agricultural Economics*. 43, supplement: 125-139.

Sobolevsky, A., Moschini, G., and Lapan, H., 2005. "Genetically Modified Crops and Product Differentiation: Trade and Welfare Effects in the Soybean Complex," *American Journal of Agricultural Economics* 87(3):621-644.

Train, K. (2009). *Discrete choice methods with simulation*. Cambridge University Press.

Trajtenberg, M. (1989). "The Welfare Analysis of Product Innovations, with an Application to Computed Tomography Scanners." *Journal of Political Economy*, vol. 97, no. 2.

UNCTAD (2006). *Tracking the Trend Towards Market Concentration: The Case of the Agricultural Input Industry*. UNCTAD/DITC/COM/2005/16, United Nations Conference on Trade and Development. http://unctad.org/en/docs/ditccom200516_en.pdf

USDA-NASS (2014). *2012 Census of Agriculture: United States, Summary and State Data*, Volume 1, AC-12-A-51, May.

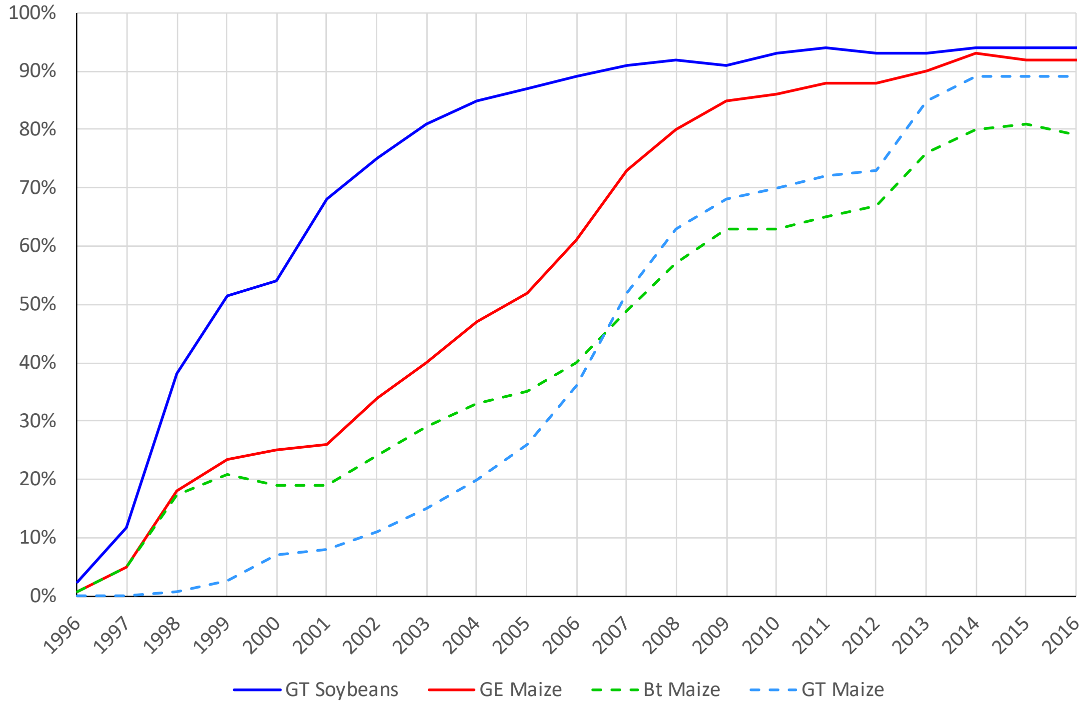
Verboven, F. 1996. "International price discrimination in the European car market." *The RAND Journal of Economics* 27(2): 240-268.

Wright, B.D. 2011. "The economics of grain price volatility." *Applied Economic Perspectives and Policy* 33(1): 32-58.

Wright B.D. 2012. "Grand missions of agricultural innovation." *Research Policy* 41(10): 1716-28.

Xu, Z., D.A. Hennessy, K. Sardana and G. Moschini, 2013. "The Realized Yield Effect of Genetically Engineered Crops: U.S. Maize and Soybean," *Crop Science*, 53:735–745.

Figure 1. Genetically Engineered Corn and Soybeans in the United States, 1996-2016



Source: USDA-NASS (2000-2016) and GfK Kynetec data (1996-1999).

Figure 2. Structure of the nested logit model

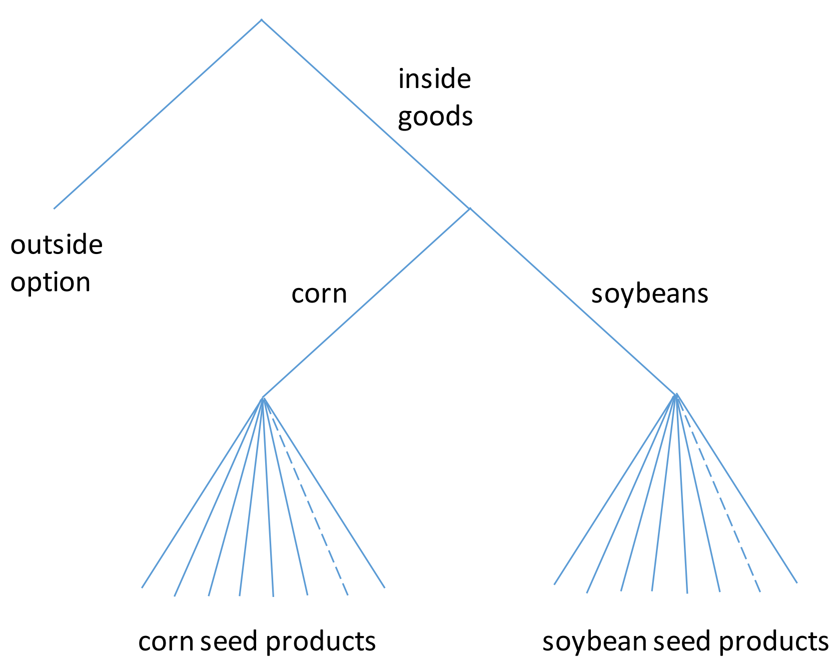


Table 1. Market Shares in the U.S. Corn and Soybean Seed Industry, 2000-2015

	2000-03	2004-07	2008-11	2012-15
CORN				
Monsanto	11.2%	21.4%	34.0%	35.4%
DuPont	36.0%	31.3%	31.5%	35.4%
Syngenta	4.7%	10.3%	7.5%	5.7%
Dow AgroSciences	5.2%	3.6%	4.1%	5.7%
AgReliant	2.5%	4.8%	6.0%	6.8%
Local & Regional Companies	40.5%	28.6%	16.9%	11.1%
SOYBEANS				
Monsanto	21.9%	23.4%	28.2%	27.6%
DuPont	19.9%	24.9%	29.3%	33.3%
Syngenta	3.4%	10.4%	10.5%	10.0%
Dow AgroSciences	1.9%	1.6%	1.9%	4.8%
AgReliant	1.1%	1.9%	1.8%	3.1%
Local & Regional Companies	41.8%	36.0%	26.8%	18.6%
Public/Saved Seed	10.0%	1.8%	1.4%	2.7%

Source: Computed from GfK Kynetec data (2000-2011), and Farm Journal Magazine (2012-2015).

Table 2. Adoption Rates for U.S. Corn and Soybeans (% of planted acres)

Year	*Soybeans*	---- *Corn Single Traits* -----			----------- *Corn stacked traits* ----------------			
	GT	*GT*	*CB*	*RW*	*GT-CB*	*GT-RW*	*CB-RW*	*GT-CB-RW*
1996	2.8%		0.7%					
1997	14.7%		5.0%					
1998	46.7%	0.7%	17.6%		0.0%			
1999	59.5%	2.4%	21.0%		0.1%			
2000	68.7%	3.4%	21.3%		0.3%			
2001	81.1%	4.9%	19.9%		1.0%			
2002	88.2%	7.0%	24.3%		2.1%			
2003	89.8%	8.7%	25.7%	0.3%	3.9%		0.0%	0.0%
2004	89.6%	12.1%	25.0%	1.0%	7.2%	0.6%	0.1%	0.0%
2005	93.1%	15.5%	24.1%	1.3%	12.8%	1.2%	0.8%	1.0%
2006	96.2%	17.8%	19.2%	1.6%	15.9%	1.9%	2.2%	4.9%
2007	96.0%	18.1%	14.7%	0.6%	20.6%	2.1%	2.8%	18.3%
2008	97.2%	18.9%	6.4%	0.1%	20.1%	0.8%	2.4%	36.9%
2009	95.5%	19.4%	4.8%	0.0%	16.6%	0.3%	2.5%	45.0%
2010	95.5%	19.8%	2.1%	0.0%	14.5%	0.3%	1.1%	50.7%
2011	96.4%	18.9%	1.2%	0.0%	16.3%	0.5%	0.5%	53.8%
Mean	75.7%	10.5%	14.6%	0.3%	8.2%	0.5%	0.8%	13.2%

Source: Computed from GfK Kynetec data.

Table 3. Seed Prices for U.S. Corn and Soybeans ($/acre)

Year	---- *Soybeans* ----		*Corn*	--- *Corn Single Traits* ---			---------------- *Corn stacked traits* -----------------			
	Non-GE	*GT*	*Non-GE*	*GT*	*CB*	*RW*	*GT-CB*	*GT-RW*	*CB-RW*	*GT-CB-RW*
1996	17.20	21.27	24.60		30.45					
1997	18.67	26.49	26.05		34.05					
1998	19.29	28.33	26.82	31.90	36.57		36.85			
1999	17.45	28.27	27.44	32.15	36.02		33.28			
2000	17.99	27.39	27.81	31.75	35.60		33.62			
2001	17.88	26.51	28.27	31.92	36.93		38.63			
2002	17.41	26.84	28.63	32.40	36.96		37.36			45.02
2003	19.35	26.18	29.82	34.06	38.21	44.78	39.18		48.88	36.30
2004	20.56	27.85	30.97	33.56	40.14	43.47	40.08	44.69	47.30	41.40
2005	21.82	32.88	31.61	36.08	38.74	42.63	41.60	44.70	47.19	49.21
2006	21.95	32.47	33.40	39.09	42.22	45.37	44.87	50.79	50.78	56.26
2007	23.43	32.86	34.31	41.54	42.62	46.08	46.01	48.08	49.27	53.21
2008	26.21	36.37	41.92	53.73	49.85	60.69	58.39	61.99	62.27	69.26
2009	35.32	46.19	47.34	63.91	55.03	41.41	68.36	67.32	67.74	86.26
2010	35.58	49.52	51.00	68.15	62.74	41.77	72.12	65.70	74.47	89.81
2011	40.62	49.70	53.86	68.69	67.42	66.21	75.09	86.25	70.72	91.32
Mean	23.17	32.44	33.99	42.78	42.72	48.05	47.53	58.69	57.62	61.81

Source: Computed from GfK Kynetec data.

Table 4. Top Brands in Corn and Soybeans, 1996-2011

Brand	Parent Company[a]	------ Corn ------ Share[b]	Price[c]	--- Soybeans --- Share[b]	Price[c]
Agrigold	Agreliant	1.88%	48.35	--	--
LG Seeds	Agreliant	1.00%	46.50	0.76%	32.74
Beck's Hybrids	Beck's Hybrids	1.07%	46.83	1.38%	36.95
Croplan	Croplan Genetics	1.66%	47.09	2.59%	33.74
Mycogen	Dow Agrosciences	3.55%	38.32	1.75%	28.13
Pioneer	DuPont	33.76%	43.21	23.86%	32.98
Asgrow	Monsanto	1.88%	34.57	16.74%	33.32
Dekalb	Monsanto	14.89%	57.18	4.75%	27.93
Fielder's Choice	Monsanto	1.68%	31.63	0.17%	44.57
Kruger	Monsanto	0.49%	51.77	1.49%	28.64
Public	Public / Universities	--		2.16%	15.32
Stine	Stine Seed	0.37%	42.49	2.92%	29.17
Garst	Syngenta	3.80%	37.68	2.12%	27.60
Golden Harvest	Syngenta	3.30%	39.01	1.85%	26.36
NK Seeds	Syngenta	4.62%	37.88	6.94%	34.90

Notes. [a] Parent company as of 2011. [b] Average share over the period considered (crop-specific percent of acres grown). [c] Average price ($/acre) of the entire period.

Source: Computed from GfK Kynetec data.

Table 5. Average Number of Seed Products in a CRD

Year	Total	Corn	Soybean	Corn with GE traits	Soybeans with GE traits
1996	10.8	6.5	4.3	0.3	0.4
1997	12.7	7.2	5.5	1.0	1.5
1998	15.0	8.1	7.0	2.0	3.2
1999	16.8	9.3	7.5	3.0	4.0
2000	18.7	10.4	8.3	4.1	4.7
2001	18.5	10.8	7.7	4.6	5.0
2002	18.0	11.1	6.9	5.3	4.9
2003	18.3	12.1	6.2	6.4	4.7
2004	19.7	13.6	6.1	8.3	4.7
2005	23.3	16.6	6.8	11.6	5.4
2006	28.2	21.4	6.8	16.2	6.0
2007	29.7	23.2	6.5	18.8	5.7
2008	27.9	21.7	6.2	18.1	5.6
2009	26.8	20.6	6.2	17.5	5.3
2010	23.5	17.3	6.2	14.7	5.3
2011	22.9	16.7	6.2	14.6	5.4

Source: Computed from GfK Kynetec data.

Table 6. Estimated Parameters of Seed Demand Models

	Nested Logit		Basic Logit	
	(1)	(2)	(3)	(4)
Price	-0.0227	-0.0151	-0.0403	-0.0049
	(0.0022)	(0.0012)	(0.0028)	(0.0005)
σ_1	0.8394	0.7983		
	(0.0090)	(0.0089)		
σ_2	0.3444	0.5985		
	(0.0572)	(0.0187)		
Soy GT Trait	0.436	0.3627	1.2950	0.8182
	(0.0333)	(0.0215)	(0.0433)	(0.0214)
Corn GT Trait	0.2101	0.1225	0.2347	-0.1380
	(0.0219)	(0.0135)	(0.0330)	(0.0149)
Corn RW Trait	0.2216	0.1473	0.4079	0.0229
	(0.0233)	(0.0152)	(0.0359)	(0.0189)
Corn CB Trait	0.1755	0.1064	0.1894	-0.1179
	(0.0184)	(0.0114)	(0.0281)	(0.0140)
Soy Dummy		-0.2354	-0.5366	-0.0294
		(0.0202)	(0.0450)	(0.0206)
Elasticities:				
Own	-7.038	-3.749	-2.109	-0.254
Cross: Within Crop	0.483	0.219	0.036	0.004
Cross: Across Crop	0.049	0.068	0.036	0.004
Cross: Outside Good	0.020	0.013	0.036	0.004
IVs?	Yes	Yes	Yes	No
Fixed Effects	Crop×Year, Crop×Brand, Crop×CRD	Year, CRD, Brand	Year, CRD, Brand	Year, CRD, Brand

Standard errors are reported in parentheses. *N*=79,260.

Table 7. Additional Results for the Nested Logit Model

	(1)		(2)	
Price	-0.0210	(0.0024)	-0.0214	(0.0024)
σ_1	0.8468	(0.0089)	0.8005	(0.0108)
σ_2	0.3750	(0.0564)	0.3143	(0.0593)
Soy GT Trait	0.4064	(0.0352)		
Corn GT Trait	0.2212	(0.0290)		
Corn RW Trait	0.2402	(0.0319)		
Corn CB Trait	0.1938	(0.0261)		
Multiple Traits	-0.0797	(0.0181)		
Soy GT Trait, 1996-2000			0.3576	(0.0400)
Soy GT Trait, 2001-2006			0.5008	(0.0387)
Soy GT Trait, 2007-2011			0.5289	(0.0382)
Corn GT Trait, 1996-2000			0.0385	(0.0412)
Corn GT Trait, 2001-2006			0.0870	(0.0280)
Corn GT Trait, 2007-2011			0.3583	(0.0341)
Corn RW Trait, 2001-2006			0.1212	(0.0361)
Corn RW Trait, 2007-2011			0.1275	(0.0277)
Corn CB Trait, 1996-2000			0.2634	(0.0270)
Corn CB Trait, 2001-2006			0.0427	(0.0429)
Corn CB Trait, 2007-2011			0.2836	(0.0305)
Multiple Traits, 1996-2000			-0.0352	(0.0981)
Multiple Traits, 2001-2006			-0.0297	(0.0231)
Multiple Traits, 2007-2011			-0.1567	(0.0210)
Elasticities:				
Own	-6.819		-5.365	
Cross: Within Crop	0.470		0.353	
Cross: Across Crop	0.049		0.043	
Cross: Outside Good	0.019		0.019	

Standard errors are reported in parentheses. *N*=79,260.

Table 8. Average Own and Cross Price Elasticities

	1996-2001	2001-2006	2007-2011
Own	-4.17	-4.72	-5.90
Cross: Within Crop	0.39	0.31	0.31
Cross: Across Crop	0.05	0.04	0.04
Cross: Outside Good	0.02	0.02	0.02

Elasticities are based on the estimated coefficients of column 2 in Table 7.

Table 9. Willingness-to-Pay for GE Products (2011 $/acre)

Trait(s)	1996-2000	2001-2006	2007-2011
Soy GT	16.68	23.35	24.66
Corn GT	1.79	4.05	16.71
Corn CB	5.65	5.94	12.28
Corn RW		1.99	13.23
Corn GT-CB	5.8	8.62	21.68
Corn GT-RW		4.67	22.62
Corn CB-RW		6.55	18.2
Corn GT-CB-RW		10.6	34.91

WTP estimates are based on the estimated coefficients of column 2 in Table 7.

Table 10. Hedonic Prices

	Parameter	Standard Error
Soybean Post GE	-1.2312	(0.6828)
Corn Post GE	-1.1468	(0.3665)
Soybean GT Trait, 1996-2000	15.4104	(0.2395)
Soybean GT Trait, 2001-2006	13.8282	(0.2407)
Soybean GT Trait, 2007-2011	11.4178	(0.3637)
Corn GT Trait, 1996-2000	11.4448	(0.4602)
Corn GT Trait, 2001-2006	10.2212	(0.1903)
Corn GT Trait, 2007-2011	13.2222	(0.1794)
Corn Borer Trait, 1996-2000	12.9633	(0.2579)
Corn Borer Trait, 2001-2006	10.2924	(0.1785)
Corn Borer Trait, 2007-2011	9.5252	(0.2287)
Root Worm Trait, 2001-2006	15.0868	(0.2961)
Root Worm Trait, 2007-2011	11.5209	(0.1978)
Multiple Traits Stack, 96-00	-7.5897	(1.6405)
Multiple Traits Stack, 01-06	-5.9030	(0.2988)
Multiple Traits Stack, 07-11	-4.5201	(0.2994)
N	79,260	
R^2	0.686	

The model was estimated with crop-year, crop-brand, and crop-CRD fixed effects, which are not reported here.

Table 11. Estimated Farmers' Welfare Gains Associated with GE Traits (2011 $)

		Keep Best		Keep Conventional		Naïve	
Period	Product Subset	Total $ (millions)	$/acre	Total $ (millions)	$/acre	Total $ (millions)	$/acre
1996-2011	All Products	14,670	2.67	22,384	4.07	43,353	7.88
	Inside Products	14,895	6.49	22,910	9.98	44,926	19.97
	Soybeans	10,689	10.33	13,388	12.93	21,703	24.12
	Corn	4,761	3.78	9,980	7.93	16,768	13.62
1996-2000	All Products	1,164	0.68	2,738	1.59	3,411	1.98
	Inside Products	1,162	1.81	2,757	4.28	3,492	5.43
	Soybeans	934	3.42	1,800	6.59	2,318	8.48
	Corn	258	0.70	1,035	2.79	1,141	3.08
2001-2006	All Products	4,817	2.33	8,340	4.03	14,363	6.94
	Inside Products	4,877	5.65	8,530	9.88	15,364	17.80
	Soybeans	4,511	11.11	5,788	14.26	9,683	23.86
	Corn	668	1.46	2,981	6.52	4,094	8.95
2007-2011	All Products	8,689	5.06	11,305	6.58	25,579	14.90
	Inside Products	8,855	11.24	11,623	14.76	26,070	33.10
	Soybeans	5,244	14.73	5,800	16.30	9,702	27.26
	Corn	3,836	8.89	5,964	13.82	11,534	26.72

Table 12. Estimated Additional Seed Industry Revenues Due to GE Traits (2011 $ millions)

Period	Crop	Keep Best	Keep Conventional	Naïve
1996-2011	Soybeans	14,105	14,016	21,738
	Corn	8,846	11,939	11,653
	Total	**22,951**	**25,955**	**33,391**
1996-2000	Soybeans	1,983	2,274	2,682
	Corn	37	274	111
	Total	**2,020**	**2,548**	**2,793**
2001-2006	Soybeans	6,779	6,809	10,027
	Corn	286	1,634	-44
	Total	**7,064**	**8,443**	**9,983**
2007-2011	Soybeans	5,343	4,933	9,029
	Corn	8,524	10,030	11,586
	Total	**13,867**	**14,964**	**20,615**